Early Detection of Cardiovascular Diseasesin ECG Images Using Convolutional Neural Networks

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Cardiovascular diseases (CVDs) account for nearly a third of all deaths globally yearly. So, early detection and type can greatly reduce the death charge by assisting in providing early and proper medication. Electrocardiogram (ECG) is a non-invasive tool, used to file the electrical hobby of the heart at normal durations. In this paper, a Convolutional neural network (CNN) is used to expect four training of sufferers: peculiar heartbeat, myocardial infarction, records of myocardial infarction, and everyday heartbeat using the general public ECG photos dataset of cardiac sufferers. The statistics used for schooling are not multiplied to large portions by any information augmentation strategies to maintain the first-class training facts. The CNN technique is investigated by way of schooling with different optimizers like Stochastic Gradient Descent with Momentum (SGDM), Root implies square Propagation (RMS-Prop), and Adaptive moment Estimation (Adam). Then, CNN is investigated through training with various initial learning rates of 0.001, 0.01, and 0.1. In keeping with the experimental consequences, the CNN with SGDM solver with aninitial learning rate of 0.1 gave an excellent validation accuracy of 95.29% in comparison to existing work with Adam as solver with an accuracy of 92.18%.

Keywords:Cardiovascular Diseases, Electrocardiogram, Convolutional Neural Network, Optimizers, Initial learning rates.

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1. Introduction

In line with the arena Heart Federation (WHF), they claim more than half a billion people around the world continue to be tormented by CVDs, which accounted for 20.5 million deaths in 2021 – nearly a 3rd of all deaths globally and an average boom on the anticipated 121 million CVD deaths[1].CVDs are the leading cause of loss of life globally[1]. The earlier they can be anticipated and categorized the more lives may be saved[2]. For analyzing the heart hobby to detect any abnormalities, there is some equipment available like an Electrocardiogram (ECG), Photoplethysmography (PPG), and so forth. This ECG is a fashionable and especially non-invasive tool for measuring the heart's electrical activity and therefore to come across CVDs.

1.1 Benefits of Artificial Intelligencein Medicine

There's an amazing capability to improve healthcare by using technologies in synthetic intelligence (AI) to reduce medical errors [3]. AI may be extraordinarily useful to patients and companies while applied within the following areas: improving care, continual ailment control, early threat identification, and workflow automation and optimization[4].AI may want to drastically lessen inefficiency in healthcare, enhance affected person glide and enjoyment, and decorate caregivers' enjoyment and affected person protection through the care pathway[5] In particular, using systems gaining knowledge of (ML) and deep studying (DL) techniques, which might be subfields of AI, for automated prediction and diagnosis of CVDs has been broadly accelerated[3].

1.2 Machine Learning Vs. Deep Learning

The ML methods can't independently discover essential features from the input information[6]. Function extraction requires an expert to select the right features before applying classification [6]. In ML, characteristic extraction is a method of lowering the whole wide variety of functions in an information set by transforming the records into a new lower-dimensional function area extracting the relevant records of the entered records. It enables the prevention of overfitting the facts and additionally improves accuracy. To expect CVDs, many ML algorithms were used like linear discriminant evaluation (LDA), aid Vector Machines (SVM), Naïve Bayes (NB), neural networks (NN), k-nearest associates (k-NN), and so forth., ML algorithms require fewer facts and much less computational strength. There are quite an excellent range of ML programs in diverse fields. laptop vision is a versatile domain of machine studying that trains machines to process, examine, and recognize visual facts. The various key sets of rules in computer vision are KNN, SVM, and Naïve Bayes. The sub-domain names of this subject are object detection, object processing, and popularity[7].

While, DL, which is an assessment of ML, routinely extracts vital capabilities and styles from the education datasets for the type segment without any additional human intervention for characteristic extraction and selection [6]. There are a few techniques in DL like Convolutional neural community (CNN), Recurrent neural networks (RNN), Multilayer perceptron (MLP), long-brief term memory networks (LSTM), etc., Deep mastering is designed primarily based on the human mind, so it may create more profound that means to information[6].The deep mastering techniques are broadly classified into four categories which encompass (i) Supervised: a mission-driven technique that makes use of labelled schooling records, (ii) Unsupervised: a facts-driven technique that analyses unlabelled datasets, (iii) Semi-supervised: a hybridization of both the supervised and unsupervised techniques, and (iv) Reinforcement: surroundings pushed technique[8].

1.3 Convolutional Neural Networks

Convolutional Neural Networks (CNNs) are a type of Deep Learning technique that has achieved groundbreaking results in various fields related to pattern recognition, such as image processing and voice recognition[9].CNNs are usually used for analyzing visual images and consist of four main components: (a) convolution layer, (b) pooling layer, (c) activation function, and (d) fully connected layer[10]. They are known to perform satisfactorily in image pattern recognition and classification. In our work, we utilized a publicly available ECG image dataset containing four different classes for detecting and classifying cardiovascular diseases (CVDs). Therefore, we chose the CNN architecture for detecting CVDs and classifying them based on the provided ECG images.

2. Literature Review

Several research studies have used ML and DL algorithms to automatically predict CVDs, utilizing ECG as a digital or visual data representation.

- C. Potes, S. Parvaneh, A. Rahman and. Conroy," Ensemble of the point- grounded and deep literacy- grounded classifiers for the discovery of abnormal heart sounds" [11].
  The authors used CNN armature for classifying normal and abnormal heart sounds. They trained the model by putrefying phonocardiogram (PCG) cardiac cycles into 4 frequency bands. Second is the AdaBoost classifier which excerpts 124 time-frequency features from PCG to train the model. The final bracket is achieved by combining both the labors and forming an ensemble of the classifiers. Their classifier ensemble has achieved an overall score of 0.8602.
- A. Nannavecchia,F. Girardi,P.R. Fina,M. Scalera, and G. Dimauro, "Particular heart health monitoring grounded on 1D convolutional neural network"[12].
  The authorsenforced a double classifier grounded on a 1D- CNN armature for detecting the anomalies in the ECG signals of the cases. After detecting any abnormality, they anatomized differentparts of ECG signals to classify the signals grounded on 21 different types of CVDs. The proposed armature has hyperparameter L2 regularisation as0.001 and validated the model using 10 cross-validation. With their proposed armature, they achieved a delicacy of 89.51%.
- Q. Zhang,D. Zhou, and X. Zeng, "HeartID: A multiresolution convolutional neural network for ECG- grounded biometricmortal identification in smart healthoperations"[13].
  The authorsconcentrated on two aspects in order to facilitate signal processing that is not dependent on the data and to perform point literacy analysis, certain steps need to be taken. To achieve this, a new seasphere multiresolution 1- D CNN is proposed. It helps in learningnatural hierarchical features from seasphere raw data without datareliance andimportantpoint selection andbirth. The model is validated and grounded on 8 ECG datasets to describe any CVDs. Through the proposed algorithm, they achieved an averagedelicacy of 93.5.
- M.B. Abubaker and B. Babayiğit," Discovery of Cardiovascular conditions in ECG Images Using Machine Literacy and Deep Literacy Styles"[14].
  The authorsconcentrated on ML and DL ways to classify 4 major CVDs grounded on ECG image datasets. They constructed two differentinfrastructures and compared the results grounded on thedelicacy achieved. originally, the transfer literacy approach was enforced withpre-trained deep neural networks like SqueezeNet and AlexNet. also, a CNN armature is enforced for detecting any CVDs. They used an Adam solver with L2 regularisation of 0.0001 as hyperparameters for training the CNN model. After comparing the results, they mentioned that the stylishdelicacy of 98.23 is achieved by the CNN model.
- U.R. Acharya,S.L. Oh,Y. Hagiwara,J.H. Tan,M. Adam, and R.S. Tan, "A deep convolutional neural network model to classify jiffs"[15].
  The authors developed a 9- 9-subcaste deep CNN to identify 5 differentorders ofjiffs in ECG signals. Thetrial was conducted on the ECG signals, analyzed in both their original form and after being downgraded to reduce noise. The sets were thoroughly analyzed to determine the exact number of cases of the 5 jiff classes and took decisive action by filtering out any noises of high-frequency.The CNN achieved a 94.03 delicacy score in the original jiffs bracket and 93.47 in the noise-free ECGs bracket, using the trained stoked data. The CNN was trained using largely imbalanced data to compare results. Delicacy of the CNN decreased to 89.07 and 89.3 in noisy and noise-free ECGs.

- S. Kiranyaz,T. Ince, and M. Gabbouj, "Real-time case-specific ECG bracket by 1- D convolutional neural networks"[16].
  The authors presented a case-specific ECG bracket and monitoring system using an adaptiveperpetration of 1- D CNNs. After training a dedicated CNN for a specific scenario, it can be used exclusively for the rapid and precise classification of potentially lengthy ECG data streams. This outcome can be readily applied for real-time ECG monitoring and early warning systems on a portable wearable device.The proposed method outperforms state-of-the-art styles in detecting ectopic beats.
- M. Zubair,J. Kim, and C. Yoon, "An automated ECG beat bracket system using convolutional neural networks"[17].
  The authors utilized Convolutional Neural Networks to introduce a bracketing system for ECG beats.The proposed recognition model of ECG patterns integrates two main features: point birth and bracket corridors.The model learns a suitable representation from ECG data, eliminating the need for hand-crafted features. Efficient classification of ECG beats into 5 classes using patient-specific training data.
- R. Bharti,A. Khamparia,M. Shabaz,G. Dhiman,S. Pande, and P. Singh, "Vaticination of heartcomplaint using a combination of machineliteracy and deepliteracy"[18].
  The authors anatomized and compared ML and DL algorithms on the UCI Machine Learning Heart Disease dataset in three different approaches. In the first method, is normal dataset that's acquired is utilized in its original form for bracket, and in the other method, the data withpoint selection are being handled and there are no data points as outliers arediscovered. Also in the third method, the dataset wasregularized ensuring that extreme values in the dataset are properly handled and don't skew the overall analysis. andpoint selection. Using deepliteracystyles with the normalized dataset, a delicacy of 94.2% is achieved.

3. Dataset

In our work, the ECG images were attained from the public ECG images database of cardiac cases(A.H. Khan and M. Hussain, "ECG images dataset of cardiac cases", Mendeley Data under the aegis of Ch— Pervaiz Elahi Institute of Cardiology Multan, Pakistan[19]. We've four different classes of case records in the data set which consists of an aggregate of 928 ECG images (see Table 1). Out of which 284 are Normal Persons(NP) images, 233 are Abnormal Heartrate(AH) images, 239 are images of persons having Myocardial Infarction(MI) and 172 are of History of Myocardial Infarction(H.MI). This particular dataset is utilized for the purpose of training and validating the CNN armature and therefore gain results and analysis from them.

Table 1. Details of public ECG image dataset [19]

S. No.	Class	No. of images
1.	Regularindividual	284
2.	Irregular Heartrate	233
3.	Heart Attack	239
4.	Past Occurrence of Heart Attack	172
	Total	928

The following figures (see Fig 1) show the sample images of the four classes NP, AH, MI, and H.MI. An NP is a healthy person who is not affected by any CVDs. An AH (abnormal heart rate) occurs whenthe heart rate isvery often irregular. When blood flow in the main artery of the heart reduces, MI occurs and therefore damages the cardiac muscles. The patients who have recently had a heart attack are classified as H.MI. Because of the unbalanced data sets available, we took an equal number of images from all 4 cases which is 172 as it is the minimum of allclasses, instead of opting for a data augmentation technique to increase thedata to a huge quantity.

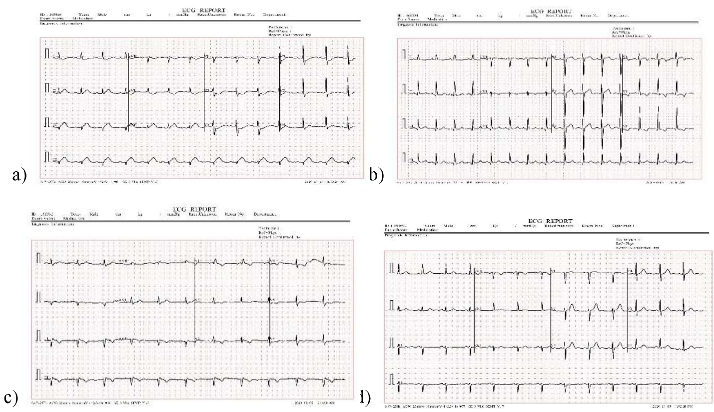

Fig.1. Samples from the ECG images dataset.(a)MI. (b) AH. (c) H.MI. (d) NP[19]

4. Methodology

4.1 Feature Extraction

Extraction of significant characteristics from input images is the primary responsibility of CNNs. The features generated by CNN have been confirmed to be more efficient and robust than handcrafted and captured features[20].CNN models usually employ two-dimensional (2-D) convolution filters to analyze grayscale imagery and red-green-blue (RGB) images[21].The pre-trainedCNN network examines and extracts distinctive features from ECG signals, such as R peaks from the last output layer of the CNN architecture,and then classifies the data by their findings. They also look for similarities between P, Q, S, and T peaks from signals belonging to the same class.

4.2 Dataset Split

We took the minimum number of images from each class of the ECG dataset to make the input data balanced instead of opting for techniques like data augmentation in previous work [14]. We chose this way to enhance the model accuracy and also to increase the chances of extending this work to detect other kinds of CVDs as well. So, we worked with 172 images in each class of ECG images and therefore 688 in total. We split the data as 70% for training and 30% for validation purposes.The validation set is utilized for tuning the hyperparameters.At the same time, the training set is used to train the CNN model.

4.3 Model Architecture

The model architecture is based on the CNN as proposed in the previous work [14] which consists of eight leaky ReLu layers, eight batch normalization layers, five dropout layers, two depth concatenation layers, one Softmax layer, three fully connected layers, three max-pooling levels and six 2-D convolutional layers in addition to one input and output layers each (see Fig 2). The architecture [14] consists of a total of 38 layers. The architecture proposed in the previous work [14] is specifically designed for analyzing ECG images. The model has been built and implemented in the Deep Network Designer, MATLABR2023a version. The model has been improved and optimized further based on input data, training, and validation parameters to acquire better results.

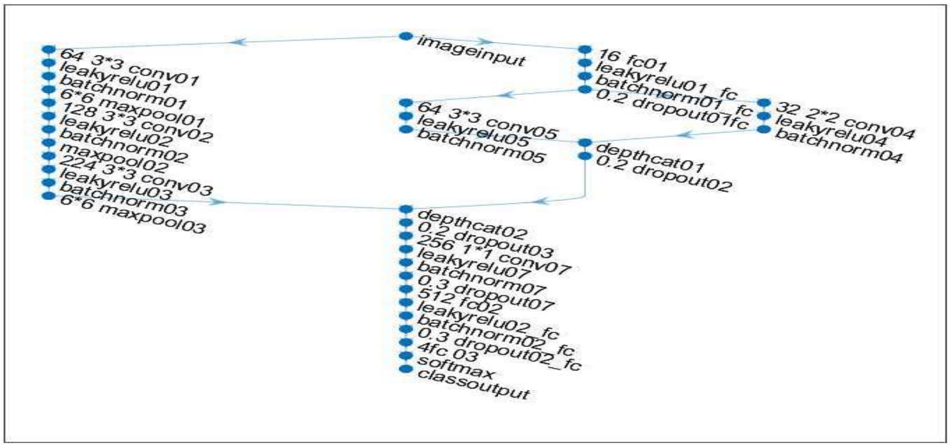

Fig.2. CNNmodel architecture [14]

4.4 Optimisation Algorithms and Learning Rates

Optimizationalgorithms are used to reduce the loss functions or to improve the efficiency of deep learning networks. They are mathematical functions that help to know how to change weights and learning rate of neural networksbasedupon the model's learnable parameters i.e.,weights andbiases. There are three popular optimizersused for image classification namely,Stochastic Gradient Descent with Momentum (SGDM), Root Mean Square Propagation (RMS-Prop), and Adaptive Moment Estimation (Adam).The performance of each optimizer varies for each image classification dataset based onthe data type and size of the dataset[22]. Each optimizer works best with its learning rate depending on its mathematical computation and also depending on the dataset.So, we're going to investigate the CNN architecture performance with various optimizers and suitable learning rates.

4.5 Model Training

We used the training set, comprising 482 images, to train the CNN model. The training is assessed with different hyperparameters like SGDM, Adam, and RMS-Prop as optimizers,initial learning rates as 0.001, 0.01, 0.1, weight initializeras Xavier, and the bias initializeras zero (see Table 2). The model gains the ability to identify ECG image patterns and features indicative of various Cardiovascular illnesses over multiple iterations. The total number of epochs is 30 and the mini-batch size is 128 to train the model. The model was trained in around 26 minutes.

Table 2. Training model hyperparameters

Optimiser	Weight Initializer	Bias Initializer	Epochs number	Mini-Batch Size
Adam	Xavier	Zero	30	128
SGDM	Xavier	Zero	30	128
RMS-Prop	Xavier	Zero	30	128

4.6 Model Evaluation

Using the values obtained through the confusion matrices, we evaluated, analyzed, and compared the validation accuracies of the model based on various parameters we discussed. The confusion matrix is obtained to determine the model's accuracy in terms of True Positive Rate (TPR), True Negative Rate

(TNR), False Positive Rate (FPR), and False Negative Rate (FNR). The format of data distribution in a confusion matrix is illustrated in the below figure (see Fig 3).

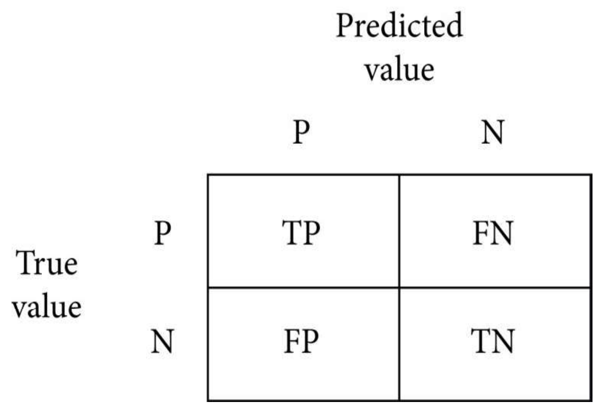

Fig.3. Confusion matrix [18]

Accuracy, sensitivity, and specificityare calculated by using the below formulae through a confusion matrix obtained.

Accuracy = (TP + TP) / (TP + TN + FP + FN) (1)

5. Results and Analysis

In CNNs, feature extraction and weight computation are automated through loads of convolution and pooling layers, removing the need for manual selection and extraction from images.In this work, CNNs automatically handle feature extraction instead of manual involvement during the training process. The training process is done with 180 iterations in total in which the validation is done for every 50 iterations and also at the end of the training process (see Fig 4). Based on training and validation processes, the modelfinally achieved an overall accuracy of 92.18% with Adam, 95.29% with SGDM, and 91.38% with RMS-Prop as solvers. The classification of CVDs in the ECG images dataset is improved by 3.11% with the SGDM solver. So, the model performed better with the SGDMoptimizerthan with the Adam optimizerin previous work [14]. The loss in prediction by the model is found to be 0.35% with the SGDM solver.The model now works better in classifying the ECG images into 4 different classes of CVDs with improved accuracy and minimized computational loss of the CNN. So, with our modified work, as given in the validation set, the model has predicted the cases of AH with 88.2%, cases of H.MI with 92.9%, cases of MI with 100.0%, and cases of NP with 100.0% as TPR, which can be visualized through the confusion matrix. This means 88.2% of AH cases, 92.9% of H.MI cases, and every case of MI and NP are correctly predicted and classified into their respective actual classes without any fault. To find the best suitable initial learning rate of SGDM for this ECG image classification using this CNN model, a comparison is also done between different initial learning rates with SGDM solver. The best accuracy is achieved by 0.1 initial learning rate i.e., 95.29%,whereas it is 89.12% and 91.76% with 0.001 and 0.01 learning rates respectively (see Table 4).So, it is found that the SGDM solver works better with a 0.1 initial learning rate for classifying ECG images dataset with a size of 172 images in each class and therefore an overall size of 699 ECG images in training and validating the CNN architecture.

Table 3. Confusion matrix for validation data (SGDM solver with an initial learning rate of 0.1)

True class/ Predicted class	AH	H.MI	MI	NP
AH	75	5	3	2
H.MI	2	79		4
MI			85	
NP				85

The confusion matrix (see Table 3) hastrue class titles in column 1 and predicted class titles in row 1. The diagonal(blue) numbers indicate the number of images predicted correctly as their respective true classes.The other numbers (orange) indicate falsely predicted or classified images as true classes.

Table 4. Table of comparison between different Initial Learning Rates

Trial	Elapsed Time	Initial learning rate	Training accuracy	Training loss	Validation accuracy	Validation loss
1	20 minutes	0.0010	100.0000	0.0221	89.1176	0.2714
2	22 minutes	0.0100	100.0000	0.0039	91.7647	0.3366
3	26 minutes	0.1000	98.4375	0.0367	95.2941	0.3556

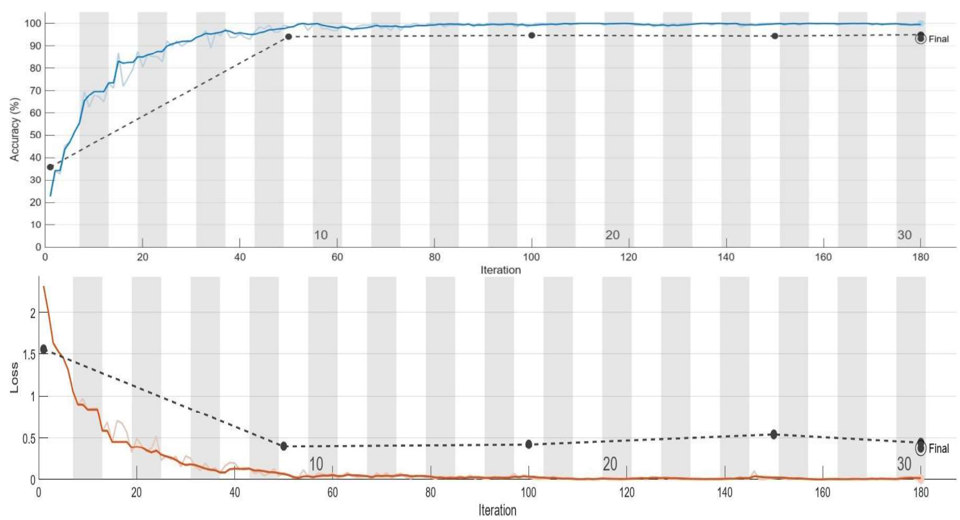

Fig.4. Training progress with an accuracy of 95.29% and loss of 0.35%

6. Conclusion

Using a public ECG image dataset of cardiac patients, we presented an efficient CNN-based model in this paper to categorize the four main cardiac anomalies, AH, MI, H. MI, and NP. The trial findings show that the CNN model performs well with improved parameters in detecting and classifying CVDs with an accuracy of 95.29%. At the same time, the accuracy achieved in the previous work [14] without performing any data augmentation is 92.18%. So, we've improved the accuracy of the model by investigating various parameters like optimizers and their suitable learning rates. This model can also be used as a tool for feature extraction in any other ECG image classification tasks with appropriate modifications and improvements. To detect CVDs with ECG images and avoid the unreliable and time-consuming findings of manual methods, clinical and cardiologists can utilize the proposed CNN model for early detection of CVDs and their diagnosis.

7. Limitations and Future Scope of Development

Although the model has predicted a few types of CVDs, the work can be extended to predict various other CVDs.The accuracy achieved isn't enough for totally relying on this model because a medical assessment of a patient has to be 100% accurate to provide accurate diagnosis to everyone. So, accuracy can also be enhanced with various other deep learning algorithms. Apart from that, a CNN model requiresa huge dataset (*in 10,000 images) for better accuracy and performance. Hence, the quantity and quality of the dataset can be improved for better results.

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