

Detection of Cardiovascular Diseases in ECG Images Using Deep Learning

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Abstract

Early intervention is important to prevent cardiovascular disease. The disease can be reduced by early detection of heart disease and clinical examination by specialists. The electrocardiogram (ECG) is an important tool for understanding the state of the human heart. The aim of this study is to develop an algorithmic model to analyze electrocardiogram signals to predict heart disease. This has the potential to improve health care at a lower cost and save lives. In this paper, we use a variety of deep learning methods to predict four types of heart disease, including heart disease history, heart rhythm, and heart disease class on a public collection of ECG images of heart patients. This paper includes a convolutional neural network (CNN) model to predict heart disease. The system for this research was developed using Mobile Net Architecture and achieved a training accuracy of 97.34% and a verification accuracy of 91.00%. As a result, the Mobile Net architecture model can classify cardiovascular diseases with high accuracy and can be used for feature extraction. A mobile net architecture model can be used to help doctors in the medical field diagnose heart disease using ECG images, replacing manual methods that result in unreliable and time-consuming results.

Keywords: MobileNet, myocardial infarction, heart rhythm abnormalities.

1. INTRODUCTION

Cardiovascular complaint is the most recent health concerto produce in the medical community. The World Health Organization (WHO) states that the biggest cause of death worldwide is cardiovascular complaint. They assert that around 10 billion people worldwide experience heart complaint each time. Heart attacks continue to be a leading cause of death encyclopedically, and if they are not treated snappily, they can affect in major health issues and indeed death.

The most recent health issue to face in the medical community is cardiovascular complaint. The World Health Organization (WHO) says that, the cardiovascular complaint is the leading global cause of mortality. They claim that every time, around 10 billion individualities around the world suffer from heart complaint. Heart attacks are still the main cause of death in the world, and if they are not treated right formerly, they can beget serious health problems and indeed death. The electrocardiogram is the primary system used to descry cardiac complaint (ECG). The electrical

exertion of the heart is measured using an ECG, which is a wide, affordable, and non-invasive system for relating cardiovascular complaint. The ECG swells can be used by a largely educated practitioner to identify the cardiac illness. This manual approach takes a long time and can produce incorrect findings. Systems are being created in the modern period for the automatic identification of cardiac-related problems, particularly the operation of machine knowledge and deep knowledge ways for the automatic prophecy of heart conditions. The pivotal factors that impact the success of these styles are points election, birth styles, type algorithm types, and utmost significantly — the use of imbalanced data for type, which might drop the non-age class's capability to be directly linked. In order to prize the maturity, if not all algorithm types, and utmost significantly — the use of imbalanced data for type, which might drop the non-age class's capability to be directly linked. In order to prize the maturity, if not all, of the information from input data, a new set of features that is amalgamation of the original characteristics into a lower dimensional space must be created. Element analysis is the most habituated point birth fashion. When machine knowledge algorithms are being trained, point selection is a procedure that eliminates irrelevant and spare information from the dataset. In order to prize the maturity, if not all, of the information from input data, a new set of features (different from the input point) must be created by combining the original features in a lower-dimensional space. Element Analysis (PCA) is the most popular point birth fashion. Yet, during the training of machine knowledge algorithms, point selection is the process of deleting pointless and spare features(confiner) from the data set. The UCI Cleveland heart illness dataset was used by the authors to study the impact of the point selection procedure on machine knowledge classifiers for predicting heart conditions. ANOVA, Chi-square, forward and backward point selection, and Lasso regression were among the several point selection styles they looked at. After that, they used six machine knowledge classifiers the DT, the arbitrary timber (RF), the support vector machine (SVM), the K-NN, the logistic regression (LR), and the Gaussian naive Bayes (GNB). The prophecy delicacy was bettered by point selection, with the backward point selection system achieving the topmost type delicacy rate of 88.52 with the DT classifier. The effectiveness of machine knowledge algorithms, analogous as NB, SVM, and DT, was examined in using 10-fold cross-confirmation on the South African heart complaint dataset. The swish results were achieved with NB, which had a delicacy rate of 71.6, perceptivity of 63 and particularity of 76.16, for detecting heart complaint. In, researchers compared NN, SVM, Bracket predicated on Multiple Association Rule, Decision Tree, and Naive Bayes algorithms to prognosticate cardiovascular conditions on two types of datasets, conforming of ultrasound images of Carotid Road ways (CAs) and HRV of the electrocardiogram signal. The combined pulled features from the Cas HRV dataset attained advanced delicacy than the separated features of CAs and HRV. SVM and CMAR classifiers outperformed the others, achieving a

delicacy rate of 89.51 and 89.46, singly. Deep knowledge, a subfield of machine knowledge, is also gaining traction in predicting cardiovascular conditions. Unlike machine knowledge, deep knowledge models automatically extract essential features and patterns from training datasets without the intervention of separate realities for point birth and selection. There is the differing generality of machine knowledge and deep knowledge. Convolutional Neural Network (CNN), a deep knowledge system, has achieved promising results in image type tasks.

2. RELATED WORK

Numerous inquiries about have been conducted for automatically foreseeing cardiovascular infections utilizing machine learning and profound learning strategies by utilizing ECG as digitals or pictures information representation.

Reference has compared machine learning and profound learning strategies on UCI heart infection dataset to anticipate two classes. Profound learning strategy accomplished the most elevated exactness rate of 94.2%. In their design of profound learning demonstrate, they utilized three completely associated layers: the primary layer comprises of 128 neurons taken after by a dropout layer with 0.2 rate, the moment layer comprises of 64 neurons taken after by a dropout layer with 0.1 rate, and the third layer comprises of 32 neurons. Whereas the machine learning strategies with highlights determination and outliers' discovery accomplished exactness rates as: RF is 80.3%, LR is 83.31%, K-NN is 84.86%, SVM is 83.29%, DT is 82.33%, and XG Boost is 71.4%. The inquire about in concluded that deep learning has demonstrated to be a more exact and successful innovation for a assortment of therapeutic issues such as pre-diction. And, profound learning strategies will supplant the conventional machine learning based on include designing. Kiranyaz et al. [3] proposed a CNN that comprised of three layers of an versatile usage of 1D convolution layers. This arrange was prepared on the MIT-BIH arrhythmia dataset to classify long ECG information stream. They accomplished exactness rates of 99% and 97.6% in classifying ventricular ectopic beats and supraventricular ectopic beats individually. Too, the work in proposed a CNN that comprised of three 1D convolution layers, three max pooling layers and one completely associated layer and one soft max layer. The channel estimate for to begin with and moment convolutional layer was set to 5 and a walk of 2 was utilized the primary two max pooling layers. They accomplished an exactness rate of 92.7% in classifying ECG heart beats utilizing MIT-BIH arrhythmia dataset.

Khan et al. [1] connected exchange learning approach utilizing the pretrained Single Shot Finder (SSD)-MobileNet-v2 to identify cardiovascular maladies from the ECG pictures dataset of cardiac patients by foreseeing the four major heart abnormalities: anomalous pulse, myocardial dead tissue, history of myocardial localized necrosis, and typical individual classes. As pre-processing steps, the

information measure was balanced and the 12 leads of each ECG picture were labeled. SSD is utilized to classify and localize the objects in one step. The dataset was part 80% for preparing and 20% for testing. They utilized a bunch estimate of 24, 200K preparing emphases for the preparing step, and a learning rate of 0.0002 to prepare their show. Their preparing stage endured nearly 4 days. They accomplished a tall accuracy rate for the myocardial localized necrosis lesson, 98.3%.

Rahman et al. [5] given a profound CNN exchange learning approach to anticipate COVID-19 and four major cardiac abnormalities utilizing ECG pictures. The dataset contained five classes: COVID-19, anomalous pulse, myocardial localized necrosis, history of myocardial dead tissue, and ordinary individual classes. Six diverse pretrained profound CNN models: ResNet18, ResNet50, ResNet101, DenseNet201, Inception-V3, and MobileNet-v2 were utilized for classification. Gamma redress, picture resizing, and z-score normalization were utilized as pre-processing steps for the ECG pictures. As a result, for two-class classification (COVID-19 and ordinary) and three-class classification (COVID-19, ordinary, and other cardiac abnormalities), DenseNet201 beat the other systems with precision rates of 99.1% and 97.36%, separately. For five-class classification, Inception-V3 outflanked the other systems with a precision rate of 97.83%. utilizing pretrained Dense Net arrhythmia classifications (anomalous pulse) from ECG signals in PTB and MIT-BIH arrhythmia datasets changed over to 2D pictures. Since the dataset was imbalanced, a information expansion method was connected to the information. The Dense Net demonstrate was chosen since it gives a arrangement to the vanishing slope issue in profound systems by utilizing thick associations between layers. Their show was alluded to as Cardio Net. The exactness, review and F1 score values were 98.62%, 98.68% and 98.65%, separately.

Avanzato and Beritelli [11] proposed a profound CNN with four 1D convolutional layers for identifying three classes of cardiac anomalies utilizing ECG signals within the MIT-BIH arrhythmia dataset. Each convolutional layer was taken after by a bunch normalization layer, a rectifier straight unit (ReLU) layer activation work, and a max-pooling layer with a channel (part) measure of 4. An estimate 80 filter was utilized for the primary convolutional layer, and the others had a channel measure of 4. This engineering did not utilize completely associated layers for classification, but instep utilized a normal pooling layer taken after by a soft max layer. This show accomplished a precision rate of 98.33%.

Acharya et al. [3] actualized a profound CNN with four 1D convolutional layers and three completely associated layers for identifying myocardial dead tissue utilizing ECG signals within the PTB dataset. In this paper, the cracked rectifier straight unit (Leaky Relu) was utilized as the actuation work layer. Each convolutional layer was taken after by a max-pooling layer with a channel measure of 2 and a walk of 2. The channel sizes for convolutional layers were 102, 24, 11,

and 9 in arrange. The number of neurons for completely associated layers was 30, 10, and 2 in that arrange. The final completely associated layer was taken after by a soft max layer. They achieved an normal exactness rate of 93.53% and 95.22% for ECG beats with and without clamor evacuation, individually. Naz et al. changed over ECG signals into 32×32 twofold pictures. Their demonstrate was tried with MIT-BIH dataset utilizing the pretrained CNN models Alex Net, VGG19, and Inception-V3 to detect ventricular arrhythmias of the heart. Exchange learning was performed to extricate and concatenate highlights from the pretrained models. SVM and K-NN classification strategies were at that point utilized for parallel classification. Utilizing the SVM, they accomplished a precision of 97.60%.

3. METHODOLOGY

3.1 Convolutional Neural Networks (CNN)

A CNN model is a specific implementation of a convolutional neural network. An architecture defines the number of layers, the layer type, the filter size, the number of filters, and the activation function used. A typical CNN model for image classification consists of the following layers:

Convolution Layer: Extracts features using a set of filters on the input image. Each filter is a small array that moves over the image to detect different patterns, such as edges and textures. Activation function: Change the output of the convolutional layer using the RELU-like function to insert the wireless network.

Source layer: The flow of the birthday layer is reduced by subtracting the maximum value from a small rectangular region of the shape map. Full Connection Layer: Assigns the output of the aggregation layer and the fusion layer to a separate class. Each neuron in a layer is connected to all neurons in the previous layer.

SoftMax layer: Generates probability distributions for possible classes.

CNN models can be trained using optimization algorithms such as backpropagation and stochastic gradient descent (SGD) to minimize the loss function, which measures how well the network predicts the correct class for an input image. There are many variations of CNN models such as VGGNet, ResNet, InceptionNet and Mobile Net. These models have different architectures and many parameters, which affect the accuracy and efficiency of the software. Some models, such as ResNet and Dense Net, use sparse or dense networks, allowing the network to learn deeper and more complex features. Other models, such as Mobile Net, use connections in deep layers to reduce the number of elements. This helps in the efficiency of the computer. Overall, CNN models have achieved breakthroughs in many computer vision tasks, including image classification, object detection, segmentation, and compositing.

In a CNN, the input image is processed by several additional layers that apply a set of filters to the input image to extract various features. The output of each convolutional layer is passed through a nonlinear activation function, such as a Rectified Linear Unit (ReLU), which introduces nonlinearity into the model [6]. After several layers, the output features are flattened and fed into one or more concatenated layers to learn how to classify the input image based on the extracted features. The output of the final connected layer is passed through the SoftMax function to generate a probability distribution over the possible classes. CNN has benefited from self-driving cars, facial recognition and medical image analysis, and computer vision.

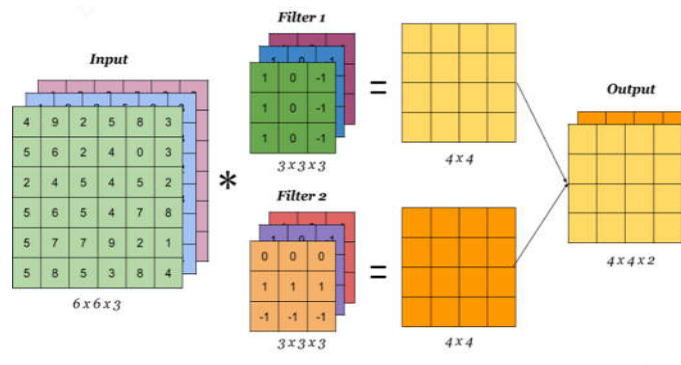


Figure 1: Example of Convolutional Operation

3.2 Pretrained Deep Learning Model

Cross learning, feature extraction and classification can be done with the help of trained deep neural networks. When a cross-learning approach is used to learn specific features of a new data set, new layers are added instead of the last layer of the trained network. The new test data set is used to test the performance metrics of the model after it is trained using a new training data set with the correct training parameters. You can use trained deep neural networks as extraction tools without wasting time and effort on training. Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Random Forest (RF) and Naive Bayes are the standard machine learning algorithms developed in this study using features removed from the trained Si units. Mobile Net is a deep neural network architecture designed for efficient and flexible image classification tasks. It was developed by Google researchers and released in 2017. The main goal of Mobile Net is to achieve high accuracy in image classification tasks and reduce the number of parameters and computational resources required for decision making. This is achieved through a combination of depth sensing segmentation and point-to-point conversion. Interpretive depth decomposition is a variant of traditional decomposition that breaks down the transformation process into two separate processes: depth perception decomposition and pointwise decomposition. A single filter is applied to each input channel using depth-optimized synthesis, while point-by-point synthesis combines the results of depth optimization using a 1×1 filter. This approach reduces the number of parameters and calculations required while maintaining accuracy. Mobile Net also uses a so-called "bottleneck" technique, which consists of 1×1

overlays to reduce the dimensionality of the input feature map before applying a more depth-aware segmentation overlay. This helps further reduce the number of parameters and computing resources required. Overall, Mobile Net has proven to be a very useful and efficient architecture for image classification tasks, especially on mobile and embedded devices with limited computing resources.

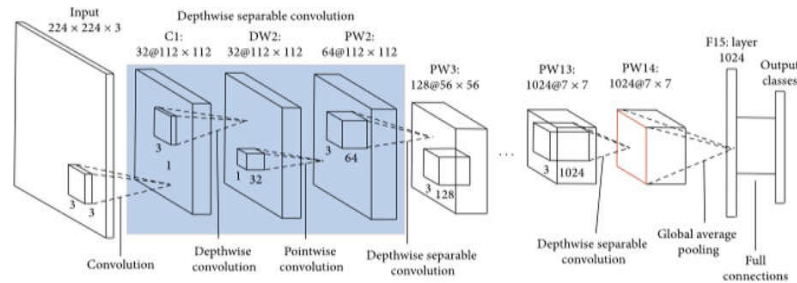


Figure 2: Image Classification MobileNet

4. IMPLEMENTATION

4.1 ECG Images Data set of Cardiac Patients

On the ECG Images dataset of cardiac patients, the aforementioned techniques were evaluated. According to the table below, this dataset includes 928 distinct patient records from four distinct groups. Normal person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction are these four categories. A healthy individual without any heart abnormalities is considered to be normal. When the electrical signals in the heart go too quickly, too slowly, or irregularly, the result is an abnormal heartbeat (arrhythmia). Heart attack, also known as myocardial infarction, happens when blood flow in the coronary artery of the heart is reduced or ceases, harming the heart muscle. The individuals with a history of myocardial infarction who have recently undergone recovery from a heart attack or myocardial infarction

4.2 Experimental Setup

Pre-processing: the dataset's ECG images include title and footer data that have no bearing on the features we need. As a result, we have submitted cropping for all photos to highlight the important details. Additionally, prior to conducting model training, all ECG images were resized to the same resolution of 227x227 with 3 channels (RGB).

Data augmentation: The dataset underwent data augmentation in order to improve the created model's accuracy and robustness. It aids in expanding the collection of pictures in the model on a balanced dataset and get rid of the impacts of doing so. The provided dataset was subjected to three augmentation methods (rotation, flipping, and translation). The dataset now contains 4,700

more pictures as a result of this.

A five-fold cross-validation was done to ensure accurate results when testing and assessing the model [10]. The dataset is split into five parts during this procedure, with four parts 3760 images were used for training, and 940 images were used for testing. The left-over portion was used for evaluation. Thus, five various categories were used to separate training from testing. The outcomes represent the mean of the five bends.



Figure 3: Samples from the ECG images dataset. (a)Myocardial infraction (b)Abnormal Heartbeat (c)History of Myocardial infraction (d)Normal Heartbeat

Table -1:

PUBLIC ECG IMAGES DATASET DESCRIPTION

No.	CLASS	Number of images
1.	Myocardial Infraction	239
2.	History Myocardial Infraction	172
3.	Abnormal Heartbeat	233
4.	Normal person	284
TOTAL	PAGE NO: 968	938

5. RESULTS AND DISCUSSIONS

Accuracy, Precision, Recall, F1 score, training and assessment times were used for performance analysis. Based on the study of the information in a confusion matrix, these measurements were made.

i) Accuracy

Accuracy is used to measure the performance and processing of the data. The percentage of outcomes that are correctly categorized can be represented by equation as follows:

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

ii) Precision:

Precision is a performance assessment that measures the ratio of correctly identified positives and to the total number of identified positives. Formula to calculate precision is:

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

iii) F-Measure/F1-Score:

The f-measure may be assumed to be the average of weights of all values. This includes both the precision and the recall.

$$F = \frac{2 \times precision \times Recall}{Precision + Recall}$$

iv) Recall:

The recall is the ratio of true positives to the addition of both true positive and false negative and can be seen as follows

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

Table-2 PERFORMANCE ANALYSIS

No.	Measures	Percentage we acquired
1.	Accuracy	91.7
2.	Recall	91.7
3.	Precision	84.3
4.	F1 score	91.7

The conception of convolutional neural networks is veritably successful in image recognition. The crucial part to understand, which sets CNN apart from conventional neural networks is the complication operation. Having an image at the input, CNN scans it numerous times to look for certain features. This scanning(complication) can be set with 2 main parameters stride and padding type. Process of the complication gives us a set of new frames, shown then in the alternate column(subcaste). Each frame contains information about one point and its presence in scrutinized image. Performing frame will have larger values in places where a point is explosively visible and lower values where there are no or little similar features. Latterly, the process is repeated for each of attained frames for a chosen number of times. In this design I chose a classic Mobile Net model which contains only two complication layers. The ultimate subcaste we're convolving, the further high- position features are being searched. It works also to mortal perception. To give an illustration, below is a genuinely descriptive image with characteristics that can be found online for CNN layers. As you can see, the operation of this model is facing recognition. The mode knows which features to seek. However, searched features are arbitrary, if you construct the CNN from the morning. Also, during training process, weights between neurons are being acclimated and sluggishly CNN starts to find similar features which enable to meet predefined thing, i.e., to fete successfully images from the training set. Between described layers there are also pooling (sub-sampling) operations which reduce confines of redounded frames. Likewise, after each complication we apply anon-linear function (called ReLU) to the redounded frame to introduce on-linearity to the model. Ultimately, there are also completely connected layers at the end of the network. The last set of frames attained from complication operations is smoothed to get a one- dimensional vector of neurons. From this point we put a standard, completely- connected neural network. At the very end, for bracket problems, there's a SoftMax subcaste. It transforms results of the model to chances of a correct conjecture of each class. We'll collect the model and apply it using fit function. The batch size will be 10. Also, we will compass the graphs for delicacy and loss. We got average confirmation delicacy of

97% and average training delicacy of 91%. We got a delicacy of 91% on test set.

A confusion matrix displays the various outcomes of a classification problem's prediction and findings in a table-like format. and helps visualize its outcomes. It gives us a table-like format of all the predicted and actual values of a classifier. This is the confusion matrix we achieved.

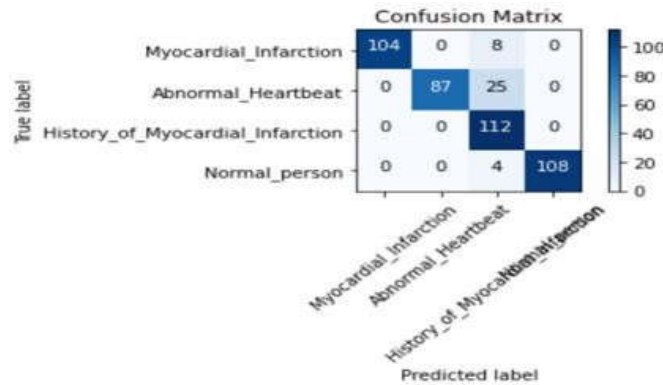


Figure 4: Confusion Matrix

6. CONCLUSION

In this research, utilizing a public ECG image dataset of cardiac patients, developed a CNN-based model to categorize the four primary cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes. The trials findings show that the suggested CNN model performs remarkably well in categorizing cardiovascular diseases and can also be used as a feature extraction tool for conventional machine learning classifiers. In order to detect heart disorders from ECG images and avoid the manual method that produces unreliable and time-consuming findings, professionals in the medical area can utilize the proposed CNN model as a tool of aid. Future research may employ optimization techniques to acquire hyperparameter values for the suggested CNN model that are optimal. The suggested model can be applied to forecasting other issues as well. Given that the suggested model's depth, parameters, and layer count all fall into the low-scale deep learning method family. Thus, a study on applying the suggested model for classification purposes in the Industrial Internet of Things (IoT) area might be investigated. Future research in this area may focus on improving the efficiency and accuracy of existing deep learning techniques, developing new models for detecting and diagnosing rare or complex cardiovascular diseases, and integrating these techniques into clinical practice. Overall, the detection of cardiovascular diseases using ECG waves using deep learning approaches holds great promise for improving the diagnosis and treatment of various heart conditions, leading to better patient outcomes and overall health.

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