Detection of Cardiovascular Diseases Using Machine Learning and Deep Learning

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Abstract
Cardiovascular diseases also known as heart diseases are the leading cause of death on a global scale. Early detection of cardiac abnormalities can save many lives and even assist physicians in developing an effective treatment plan. An electrocardiogram (ECG), a common and inexpensive way of detecting the electrical activity of the heart, can be used to diagnose cardiovascular diseases. Numerous studies have been conducted on the use of machine learning algorithms to detect heart disease, though the majority of these models do not provide especially high accuracy. This project used the publicly available ECG image dataset of cardiac patients to identify four main cardiac abnormalities: myocardial infarction, history of myocardial infarction, abnormal heartbeat, and normal person classes.

1. Introduction

Cardiovascular diseases (a.k.a. heart diseases) are the main cause of death worldwide, according to the World Health Organization (WHO). They cause an estimated 17.9 million fatalities annually, or 32% of all deaths worldwide. Over 85% of all heart disease-related deaths are caused by myocardial infarctions, also known as heart attacks. Early detection and treatment of coronary disease can save many lives. To detect heart disorders, the healthcare system uses a variety of techniques, including electrocardiography (ECG), echocardiography, cardiac magnetic resonance imaging (MRI), computed tomography (CT), blood tests, and others. A common, inexpensive, and non-invasive method for detecting the electrical activity of the heart is the electrocardiogram (ECG). It is used to identify cardiovascular diseases that affect the heart. A highly seasoned practitioner can use ECG waves to diagnose cardiac illness. However, this manual process takes a long time and can result in incorrect outcomes. The use of artificial intelligence in healthcare has the potential to drastically lower medical mistakes. The automated detection of heart diseases using machine learning techniques and in particularly deep learning techniques. Deep learning methods were used in this study to identify four main cardiac abnormalities: myocardial infarction, history of myocardial infarction, abnormal heartbeat, and normal person classes.

2. Literature Review

Numerous researches have been conducted for prediction and detection of heart diseases using machine learning and deep learning.

Reference [1] shows the various applications of data mining techniques in the healthcare field. Spread of infectious diseases can be monitored and automated surveillance systems were proven to have more advantages. Thus it was concluded that machine learning has a huge scope in the medical field. [2] develops a system which extracts any hidden information or knowledge from a historical heart disease database. The models are evaluated using the Lift Chart and Classification Matrix approaches. Naive Bayes model was used and showed 86% accuracy. This system was developed to help doctors in making better decisions and reduce medical error.

Nikhar and Karandikar [3] studied the prediction of heart diseases using the Decision Tree and

Naive Bayes classifiers. The Decision Tree classifier had better accuracy compared to Naive Bayes due to information gain calculations. The performance of Naive Bayes classifier could be increased with the use of Selective Naive Bayes classifier. The work in [4] shows the comparison between Naive Bayes, Support Vector Machine, Artificial Neural Networks, Simple Logistic Regression and Random Forest and they showed accuracy of 86.4%, 97.53%, 77.89%, 95.05% and 95.67% respectively. The precision, recall and sensitivity were also calculated and SVM always showed the best results. A real-time monitoring system using Arduino was developed, display monitor, buzzer, different biomedical sensors, etc which took gender, age, blood sugar, blood pressure, chest pain type, serum cholesterol, etc as input and using the SVM algorithm detected the existence of any heart disease. In [5], Ramalingam conducted a survey of various machine learning algorithms such as Naive Bayes, K – Nearest Neighbour, Support Vector Machine, Decision Tree and Random Forest and analyzed their performance. It was concluded that machine learning algorithms have a huge potential for predicting cardiovascular disorders. In some cases, decision trees performed extremely poorly, which could be caused by overfitting. Random Forest models performed exceptionally well because they solve the problem of overfitting by using several algorithms. Naive Bayes classifier-based models had good performance and were computationally quick. For the most part, SVM performed well.

In [7], the machine learning algorithms used for heart disease prediction and python programming were analyzed. K- Nearest Neighbor, Decision Tree Classifier, Random Forest Classifier, Correlation, SVM were analyzed and showed accuracy of 63.4%, 71.4%, 68.4% and 86.2% respectively. Shashwith et al. [8] presented a study on different machine learning algorithms such as Naive Bayes, Decision Tree, Logistic Regression and Support Vector Machine with test accuracy of 49.18%, 81.97%, 88.52% and 90.16% respectively e using UCI machine learning repository dataset. The work in [9] shows the classification of different cardiac diseases using 12-lead-based ECG images divided into four classes. SSD MobileNet V2 was used to train the detector which had an accuracy of 98.33%. In [10], Anwar et al. discussed the effect of picture augmentation on ECG images. Efficient Net B3 was used to classify the images into four classes: COVID, Normal, Myocardial infarction, and history of Myocardial Infarction. The highest accuracy was achieved with AdamW optimizer which was 0.818 but that was reduced to 0.002 when flip augmentation was applied. While image augmentation techniques are used to expand data, they may cause hidden data patterns to be distorted, which lowers performance.

In [11], Aspuru et al. provided a method based on the use of linear regression to divide the data into periods in order to identify the P, Q, S, and T peaks before segmenting the signal to identify the R point of the ECG wave. The pre-processing of the ECG signal to remove noise allowed the system to effectively locate fiducial points, which is essential to diagnose cardiac problems using machine learning classifiers. 260 ECG signals were analyzed and an average sensitivity of 99.5% was obtained to identify all P, Q, R, S and T peaks.

Acharya et al. [12] created a deep CNN with four 1D convolutional layers and three fully connected layers to detect myocardial infarction using ECG signals from the PTB dataset. The leaky rectifier linear unit served as the activation function layer in this model. They were able to attain average accuracy rates of 93.53% and 95.22% for ECG beats with and without noise removal, respectively.

3. Methods

A. Convolutional Neural Networks (CNN)

A deep learning technique known as a convolutional neural network (CNN) is particularly adept at image and pattern recognition tasks. Convolutional layers, pooling layers, and completely connected layers are among the many layers that make up this structure. Fundamentally, the CNN filters are how the algorithm finds the pattern. Similar to any other block or collection of blocks where we can specify patterns, these filters are just blocks. We start by comparing the image's pixel to the filter's pixel, then move on to the following pixel and vote through all of the pixel layers until we have not every block. It only offers us an array of integers that indicate how closely the image fits the filter, and that's only for one filter. Similarly, we can increase the number of filters to get a new shape or pattern. We can now gain a much better grasp of what is contained within this series of pixels if we pool together the numeric arrays from each of these filters.The filters grow more abstract or have more capabilities as we delve deeper into the neural network; after all, this was only the first layer in the CNN. So, the second layer filters may be able to carry out tasks like fundamental object recognition. In the second layer, we can add more filter sets that perform related functions. Hence, as we go deeper into the CNN, the following layer might carry out even more ethereal functions, including intricate object recognition. As a result, we can observe how the application of these filters grows as we move through the network and complete trickier jobs.

The main duty of CNNs is to extract important properties from input images. The two major components of CNNs are convolutional layers and pooling layers. A sigmoid or softmax activation function layer serves as the final layer in CNNs to produce the desired results. In CNNs, the upper levels could be entirely connected layers. Convolution is carried out by applying the filter to the input. Each time the matrix is multiplied, the result is added as a sum to the feature map (Fig. 1 shows a simple example of a convolution process for an input with a depth of 1).

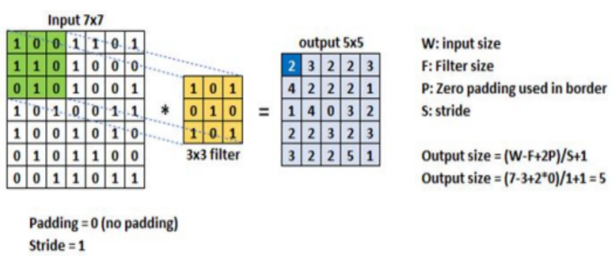


FIGURE 3.1 An example of Convulational Operation

B. Mobilenet Architecture

In order to effectively integrate Computer Vision into compact, portable devices like mobile phones and robots without noticeably compromising accuracy, Google researchers created the MobileNet CNN architecture in 2017. In comparison to some of the other CNN architectures, the standard MobileNet has 4.2 million fewer parameters overall. By introducing two new global hyperparameters that can be tuned based on the needs of the model developer, MobileNets also gives model developers the flexibility to control the size of their model (at the expense of accuracy) depending on their needs.

To make the model smaller and less difficult in mobilenets, depthwise separable convolutions are employed in place of normal convolutions. A given input is subjected to two steps of a depth wise separable convolution:

i. Depthwise Convolutional

During depth-wise convolution, each channel of the input image is handled separately. If the input image were of dimension DF DF M (where M is the number of channels), then we would require M filters of dimension DK DK 1. (It should be noted that each filter will be applied to only one channel of the input image). After a depthwise convolution, M matrices of dimension (DF-DK+1) (DF-DK+1) 1 will be generated from the input image. After stacking these matrices, we get a single output matrix with dimensions (DF-DK+1) (DF-DK+1) M.

ii. Pointwise Convolutional

On the output of the depthwise convolution layer, the pointwise convolution layer applies "N" filters of dimension 11M. As a result, an image of the dimensions (DF-DK+1) (DF-DK+1) N is produced. Increasing the output image's number of channels is the goal of utilising 1 to 1 filters. So, DK, DK, M, (DF-DK+1) (DF-DK+1), (DF-DK+1)+M, N, (DF-DK+1), (DF-DK+1) would be the total cost of computing. Contrarily, a conventional convolution filters and combines the values of the several input image channels in a single step. As the input image's dimension is DF DF M, the comparable conventional convolutional layer of the depth-wise separable layer described above would have N filters of dimension DK DK M. Moreover, this would provide an output image with the dimensions (DF-DK+1) (DF-DK+1) N. The entire cost of the calculation will result in DK × DK × M × N × (DF-DK+1) × (DF-DK+1).

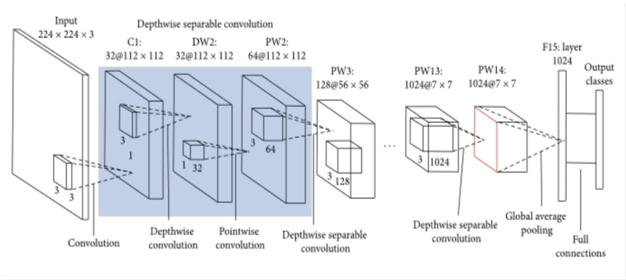


FIGURE 3.2 **The Mobile Net Architecture**

Type / Stride	Filter Shape	Input Size
Conv / s2	3 × 3 × 3 × 32	224 × 224 × 3
Conv dw / s1	3 × 3 × 32 dw	112 × 112 × 32
Conv / s1	1 × 1 × 32 × 64	112 × 112 × 32
Conv dw / s2	3 × 3 × 64 dw	112 × 112 × 64
Conv / s1	1 × 1 × 64 × 128	56 × 56 × 64
Conv dw / s1	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 128	56 × 56 × 128
Conv dw / s2	3 × 3 × 128 dw	56 × 56 × 128
Conv / s1	1 × 1 × 128 × 256	28 × 28 × 128
Conv dw / s1	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 256	28 × 28 × 256
Conv dw / s2	3 × 3 × 256 dw	28 × 28 × 256
Conv / s1	1 × 1 × 256 × 512	14 × 14 × 256
5× Conv dw / s1	3 × 3 × 512 dw	14 × 14 × 512
5× Conv / s1	1 × 1 × 512 × 512	14 × 14 × 512
Conv dw / s2	3 × 3 × 512 dw	14 × 14 × 512
Conv / s1	1 × 1 × 512 × 1024	7 × 7 × 512
Conv dw / s2	3 × 3 × 1024 dw	7 × 7 × 1024
Conv / s1	1 × 1 × 1024 × 1024	7 × 7 × 1024
Avg Pool / s1	Pool 7 × 7	7 × 7 × 1024
FC / s1	1024 × 1000	1 × 1 × 1024
Softmax / s1	Classifier	1 × 1 × 1000

4. Experiments

A. The Dataset of ECG Images of Patients

The dataset acquired consists of nine hundred twenty eight unique patients records. The methods which were previously discussed were applied and tested on these dataset.This dataset has four different classes each class showing a different cardiac condition. The labels for these classes are: (a)Myocardial Infarction (b)History of Myocardial Infarction (c)Abnormal Heartbeat (d)Normal Person, which can be seen in Fig.4.1.

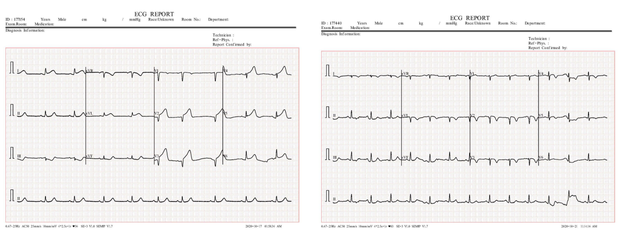
Myocardial Infarction which is commonly known as heart attack is a condition where the blood flow in the coronary artery is affected (blood flow decreases or stops) usually due to unhealthy lifestyle. History of Myocardial Infarction refers to the patient who recently recovered from the aforementioned condition. Another cardiovascular condition is the abnormal beating of the heart, this condition is also called arrhythmia, it is when a person's impulses emitted from the heart are irregular where it can sometimes be too fast or too slow. Finally we have the reports of the normal patients who do not suffer from any of the cardiac conditions.

B. Experimental Settings

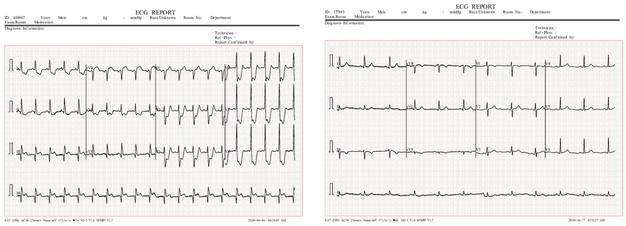
The experiments are performed on visual studio code on AMD Ryzen 5 5600H with Radeon Graphics, 3301 Mhz, 6 Core(s), 12 Logical Processor(s) running on Microsoft Windows 11.

The preprocessing is applied to the dataset, we can see in figure 4.1 the image dataset consists of extra information above the actual reading which is not necessary for the model.So by applying the preprocessing we crop out those information and just keep the actual readings for the model to work on. All images were brought to the same size of 277x277.

Next is data augmentation, it is applied to the dataset inorder to increase the functioning and accuracy of the model. It does so by increasing the number of images in the dataset by reusing the images by temporarily changing the orientation of that image like rotation and flipping .



(a) (b)



(c) (d)

FIGURE 4.1 Samples of ECG images from the dataset (a)Myocardial infarction (MI) (b)History of myocardial infarction (HMI) (c)Abnormal heartbeat (AH) (d)Normal person (NP)

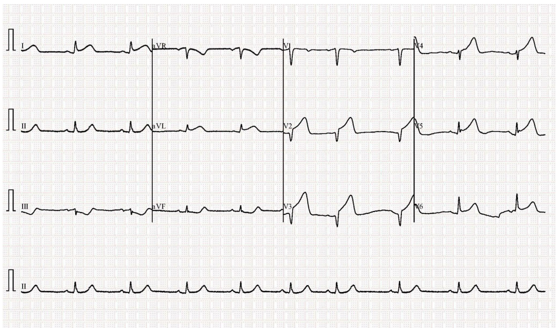


FIGURE 4.2 A Sample of ECG image after performing cropping as a preprocessing.

PUBLIC ECG IMAGES DATASET DESCRIPTION.

No.	Class	Number of images
1.	Normal person	284
2.	Abnormal Heartbeat	233
3.	Myocardial Infarction	239
4.	History of Myocardial Infarction	172
Total		928

5. Results

We trained our algorithm on a workstation with AMD Ryzen 5 5600H with Radeon graphics processors and 8 GB RAM for this research. Accuracy, precision, recall, F1 score, training, and testing timeframes were used for the project's performance study. These evaluations are based on an examination of data from a confusion matrix, where Accuracy is defined as the ratio of correctly forecasted observations to all observations. Precision is defined as the percentage of correctly classified positive samples (True Positive) to the overall number of positively classified samples. (either correctly or incorrectly).

Precision equals False Positive plus True Positive plus True Positive
The recall is calculated by dividing the proportion of Positive samples accurately identified as Positive by the total number of Positive samples. The recall metric measures how well the model can detect positive data. The greater the number of positive samples found, the greater the recall.
True Positive/True Positive plus False Negative equals Recall

The weighted average of Precision and Recall is the F1 score. As a result, consideration is given to both false positive and false negative values.
Fig. 5 depicts the analysis of the confusion matrix for all four dataset classes that we took into consideration in our case, the ECG pictures dataset of cardiac patients. The equations listed in Table 1 are used to calculate the experiment success metrics.

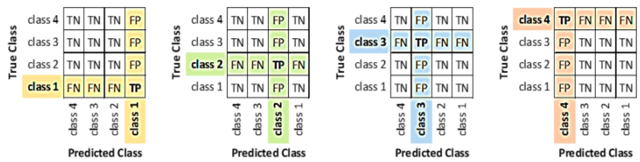


FIGURE 5 The semantic of the Confusion matrices for 4 classes results.

TABLE I

PERFORMANCE MEASURES.

Measures	Defined as	
Accuracy	$(TP+TN)/(TP+FP+FN+TN)$	(1)
Recall	$TP/(TP+FN)$	(2)
Precision	$TP/(TP+FP)$	(3)
F1 score	$(2 \times Recall \times Precision)/(Recall+Precision)$	(4)

6. Conclusion

With the help of the results we found the experiments performed using the the lightweight

CNN model achieves remarkable outcome in the classification of different cardiovascular diseases which are Myocardial Infarction, History of Myocardial Infarction and Abnormal Heartbeat, using the patient's ECG report as the dataset. We can also conclude that the proposed model can be used as a tool by medical professionals to more accurately obtain the diagnosis of the patient. This may help to avoid the manual labor which could lead to inaccurate results, which could also be very time consuming .

The model could be further worked on by applying the necessary optimization techniques to obtain better results. This model could also possibly be used to detect/predict other types of problems by tweaking its parameters and replacing its dataset with the one which is appropriate for the scenario.

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