DEEP LEARNING FOR CARDIAC DISEASE DETECTION

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Abstract : This study aims to provide clinicians with a powerful tool for detecting cardiac problems at an early stage, using deep learning and machine learning techniques. By doing so, appropriate medication can be administered to patients with minimum negative impact. Heart disease has become a significant health concern in recent years due to unhealthy lifestyle choices and the accumulation of fat in the heart. Deep learning algorithms can analyze various features of a dataset to predict the likelihood of heart disease. The primary objective of this system is to enhance the accuracy of diagnosing heart disease through deep learning, where the dependent variable indicates whether a person has cardiovascular disease or not.

Key Words- Deep Learning, Cardiac disease detection, predictive model, medical field, CNN.

1. INTRODUCTION

Accurate analysis of heart function is crucial for clinical cardiology in patient care, disease diagnosis, risk assessment, and therapy selection, especially since cardiovascular disease is the leading cause of death globally. The heart, a pumping organ, plays a critical role in distributing blood to various organs and tissues to supply nutrients and oxygen while removing metabolic waste products. However, as people age, their hearts become less efficient, leading to cardiovascular disease in some cases. Valvular heart diseases, which can be caused by valve defects or inadequacy, affect heart function by impeding blood flow and are a common problem, especially in developed countries[1].

Early stages of valvular heart disease usually exhibit no apparent clinical symptoms, but as the condition worsens, it can have a significant impact on physical health. Therefore, medical practitioners are keen on developing effective strategies for detecting cardiac disease[9]. Electrocardiography (ECG) is a diagnostic tool that can examine heart rhythm abnormalities using electrodes placed on the skin's surface. By analyzing numerous potential fluctuation signals and their correlations, ECG can predict the heart's physiological condition and function[7].

Echocardiography is another widely used diagnostic tool that can produce real-time 2D or 3D images of the heart and its contractions, making it a valuable tool when combined with ECG. This technique uses sonic sensors to detect successive sound waves and reconstructs the internal tissue composition and body mass through computerized computations. Dynamic graphics can also be generated by combining various images, providing doctors with valuable clinical diagnostic information[3].

2. ALGORITHM

The algorithm involves the following steps:

Step 1: Collecting Dataset

During the first module, a system was developed to gather input datasets for both training and testin purposes. The dataset, which consists of 1377 electrocardiogram (ECG) images, is included in the model folder[8].

Step 2: Import required libraries

Python programming language will be utilized for the task, and we will begin by importing various essential libraries required for this project. These libraries include Keras, which will be used to create the primary model, Scikit-learn for dividing the data into training and testing sets, PIL for transforming images into arrays of numerical values, as well as other essential libraries like Pandas, NumPy, Matplotlib, and TensorFlow[4].

Step 3: Getting Images

We will get the Images as well as their labels. The Image should then be resized to (224,224), as all images must be the same size for recognition. The photos should then be converted into a numpy array.

Step 4: Splitting the dataset:

Divide the dataset into train and test halves. There is 80% train data and 20% test data.

Step 5: MobileNet or CNN model

MobileNet is a deep convolutional neural network (CNN) architecture focused on efficiency and compactness for mobile and embedded devices. It was created by Google researchers and released in 2017.

Depthwise separable convolutions, a type of factorised convolution that separates spatial and channel-wise operations in a convolutional layer, are used in the MobileNet architecture. This minimises the amount of parameters and computations needed while retaining high precision. The MobileNet design additionally employs a mix of 1x1 pointwise convolutions and global average pooling to further minimise the amount of parameters and processing[6].

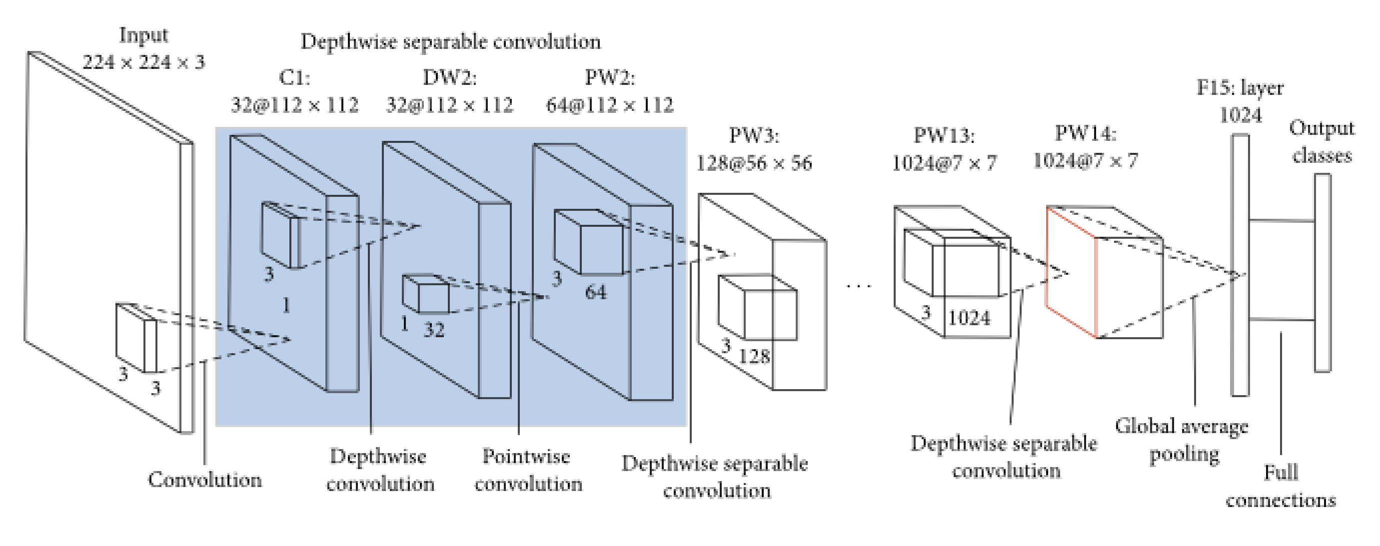

figure 2.1: Image Classification using the Mobilenet

Step 6:Apply the model and plot the graphs for accuracy and loss-

We will build the model and apply it using the fit function. The batch size will be ten. Then we'll draw the graphs for accuracy and loss. We obtained an average validation accuracy of 97.00% and an average training accuracy of 91.00%.

3. Architecture:

Depthwise separable convolutions are used by MobileNet.When compared to the network with regular convolutions of the same depth in the nets, it significantly reduces the number of parameters. As a consequence, lightweight deep neural networks are created.
Two procedures are used to create a depthwise separable convolution.

1. Depthwise Convolution
2. Pointwise Convolution

The depthwise separable convolution can be defined mathematically as follows:

$$Y = \text{Pointwise}(\text{Conv}(\text{Depthwise}(X, W\_d), W\_p))$$

where:

X is the input feature map
W_d is the depthwise convolution filter
W_p is the pointwise convolution filter
Depthwise is the depthwise convolution operation
Pointwise is the pointwise convolution operation
Y is the output feature map

3.1 Depthwise Convolution:

Depthwise convolution generates a collection of intermediate feature maps by applying a different filter to each input channel of a feature map. It is mathematically defined as follows:

$$Y = \text{Depthwise}(X, W\_d)$$

where:

The input feature map is denoted by X,The depthwise convolution filter is denoted by W_d,Y is the final feature map.

3.2 Pointwise Convolution:

The pointwise convolution takes the intermediate feature maps and performs a 1x1 convolution on them, resulting in a single output feature map. Mathematically, it is as follows:

$$Y = \text{Pointwise}(X, W\_p)$$

where:

The input feature map is denoted by X,The depthwise convolution filter is denoted by W_d,Y is the final feature map.

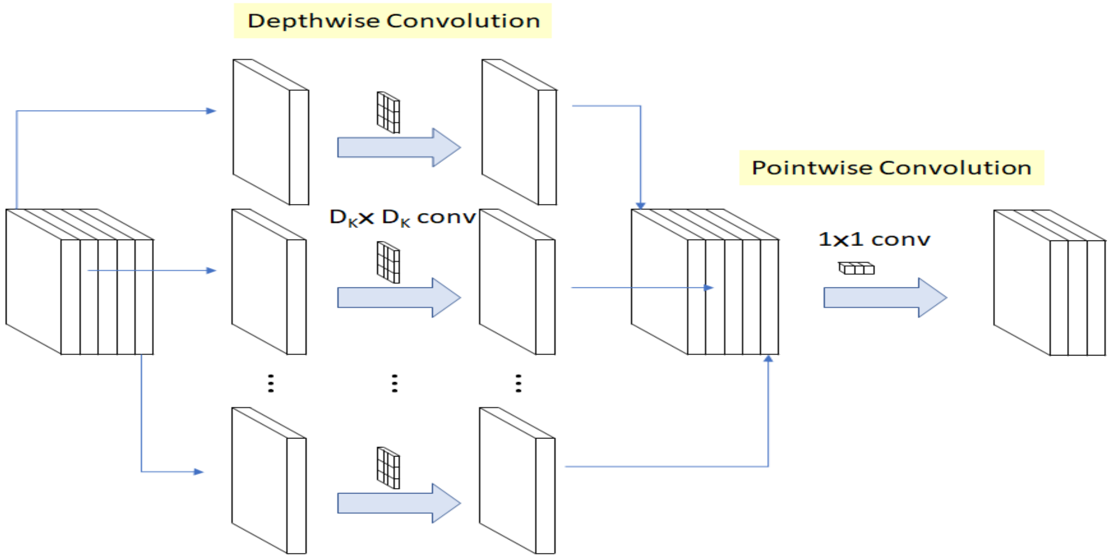

figure 3.1: Depthwise separable convolution

3.3 Flow Chart

A flowchart is a diagrammatic depiction of a process's steps in a sequential order. It is a tool for defining a range of operations, such as a manufacturing process, a service method, or a project plan.

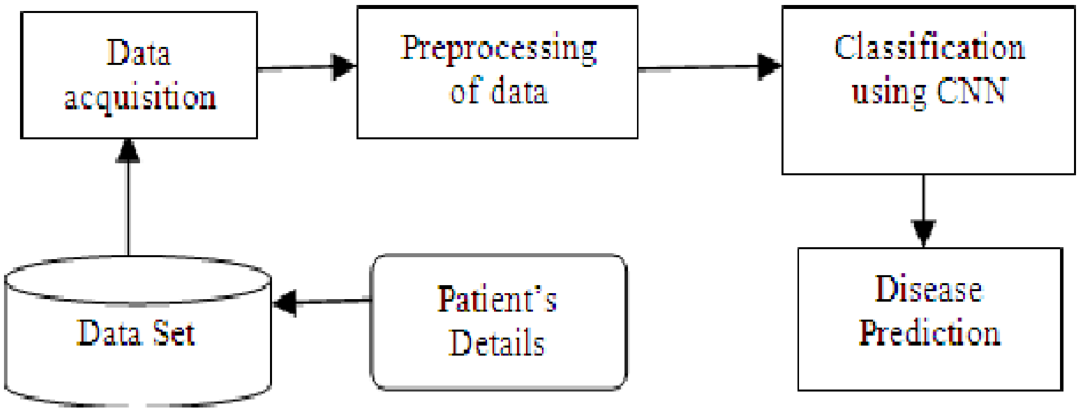

figure 3.3.1:Diagram Depicting Project Flow

4. WORKING:

Convolutional neural networks have been proven to be highly effective in image recognition, with the convolution operation being the key component that sets them apart from regular neural networks. The CNN scans an image several times to identify specific features, with two key parameters for this process being the stride and padding type. As the CNN convolves higher layers, it searches for more high-level features, similar to human perception. During the training process, the weights between neurons are adjusted, and the CNN gradually learns to recognise the searched features. At the end of the network, there are fully connected layers, and the final set of convolution frames is flattened into a one-dimensional vector of neurons. A softmax layer is included at the end for classification purposes, converting the model results into probabilities of valid class guesses, such as normal heart rate, abnormal heart rate, or myocardial infarction.

5. RESULTS:

The model's final output tells the customer whether the patient has heart illness or not. Accuracy depends on the quality of the ECG pictures. We will build the model and use the fit function to apply it. There will be ten batches. The graphs for accuracy and loss will then be plotted. We obtained 97.00% average validation accuracy and 91.00% average training accuracy. Furthermore, medical professionals should make the final decision on any outcome.

The convolution operation is the essential feature that distinguishes convolutional neural networks from conventional neural networks and has been demonstrated to be extremely effective in image recognition. The stride and padding type are two crucial factors in the CNN's many scans of an image to recognise specific features. The CNN looks for more high-level traits as it convolves higher layers, just like a person would. The weights between neurons are changed as part of the training process, and the CNN eventually gains the ability to detect the searched features. The final set of convolutional frames are flattened into a one-dimensional vector of neurons at the network's end, where there are fully linked layers. At the conclusion, a softmax layer is added for categorization.

5.1 Output Snapshots:

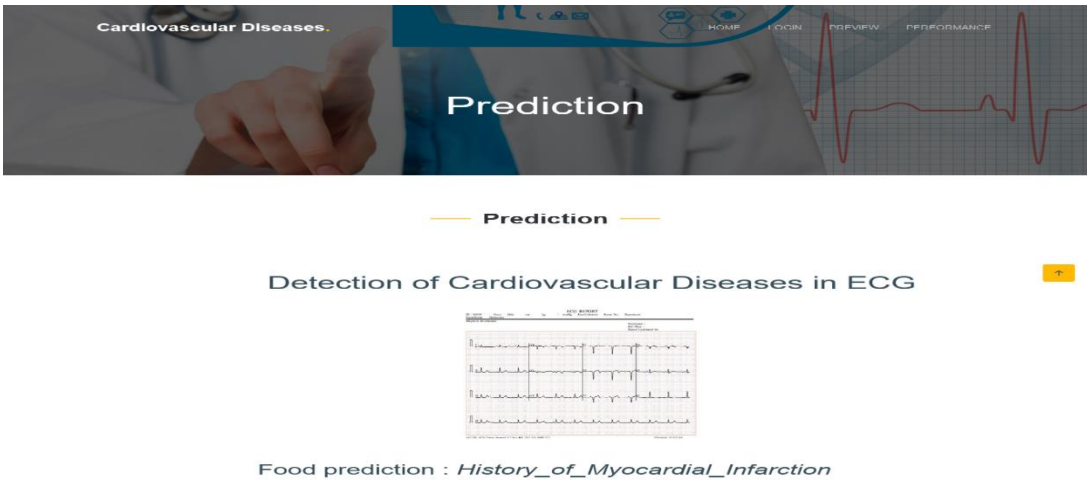

figure 5.1.2: figure shows the model predicted the ECG as HISTORY_OF_MYOCARDIAL_INFRACTION

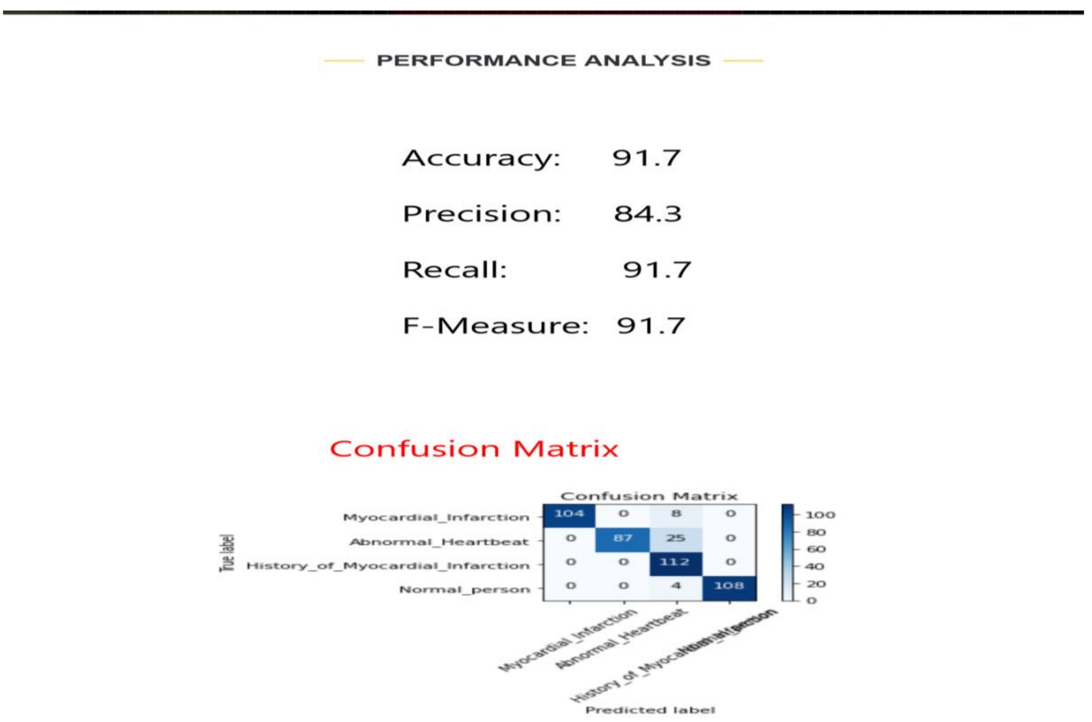

figure 5.1.3: shows the final precision and accuracy of the model.

6. CONCLUSION

Finally, the application of deep learning models like MobileNet for heart illness diagnosis has yielded encouraging results. Several studies have shown that these models are capable of properly diagnosing different cardiac problems such as arrhythmias Myocardial infraction ,Abnormal heartrate and Normal heart rate.

MobileNet, in particular, is a lightweight deep learning architecture that has proven to be effective in a variety of computer vision applications, including medical imaging. Its economical architecture allows it to function on mobile devices, making it especially suitable for real-time cardiac diagnostics and remote monitoring.

While deep learning models such as MobileNet are not currently commonly employed in clinical practise, they have the potential to improve the accuracy and efficiency of cardiac illness diagnosis. More research and development in this area will be required to realise these models' full promise for improving patient outcomes and lowering healthcare expenditures.

7. REFERENCES:

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