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Deep Learning Framework For Early Identification Of Cardiac Abnormalities From Ecg Images

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ABSTRACT

Over the past few decades, cardiovascular illnesses have become the leading cause of death worldwide in both industrialized and developing nations. The mortality rate can be decreased through early identification of heart disorders and ongoing clinical monitoring by professionals. Cardiovascular disease is extremely lethal by nature and kills a disproportionately large number of people worldwide. An effective early detection strategy is crucial to preventing cardiovascular disease deaths. An electrocardiogram (ECG) is a vital tool for understanding a variety of human heart problems. This subject has been the subject of numerous investigations to identify heart anomalies for prevention. In order to forecast cardiovascular disorders, this research intends to construct an algorithmic model to analyses ECG tracings. This effort directly affects saving lives and enhancing healthcare at a lower cost. Saving lives and enhancing medical treatment are two immediate effects of this work as health care and health insurance expenses rise globally. In this study, the public ECG picture dataset of cardiac patients was used to harness the potential of deep learning techniques to predict the four main cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes. We used the Mobile Net Architecture to build the system for this project, and we were successful in achieving training accuracy of 97.34% and validation accuracy of 91.00%. As a result, the proposed Mobile Net Architecture model classifies cardiovascular diseases with impressive accuracy and can also be utilized to extract features for conventional machine learning classifiers. Bypassing the manual method that produces unreliable and time-consuming findings, the suggested Mobile Net Architecture model can be utilized as a tool to assist physicians in the medical profession in detecting heart disorders using ECG images.

Keywords: *Cardiovascular Disease (CVD), Electrocardiogram (ECG), Deep Learning, MobileNet Architecture, Cardiac Abnormalities, Abnormal Heartbeat, Myocardial Infarction, Image Classification, Medical Diagnosis, Feature Extraction*

1. INTRODUCTION

According to the World Health Organization (WHO), cardiovascular diseases (heart diseases) are the leading cause of death worldwide. They claim an estimated 17.9 million lives each year, accounting for 32% of all deaths worldwide. About 85% of all deaths from heart disease are due to heart attacks, also known as myocardial infarctions. Many lives can be saved if efficient diagnosis of cardiovascular disease is detected at earlier stage. Different techniques are used in healthcare system to detect heart diseases such as electro-cardiogram (ECG), echocardiography (echo), cardiac magnetic resonance imaging (MRI), computed tomography (CT), blood tests, etc. The ECG is a common, inexpensive, and noninvasive tool for measuring the electrical activity of the heart. It is used to identify heart related cardiovascular diseases. A highly skilled clinician can detect heart disease from the ECG waves. However, this manual process can lead to inaccurate results and is very time-consuming.

There are various methods that can be used for feature selection which are classified as unsupervised, which refers to the method that does not need the output label for feature selection, and supervised, which refers to the methods that uses output label for feature selection. Under supervised feature selection, there are three methods: the filter method, the wrapper method and the embedded method. Many machine learning methods have been used for predicting cardiovascular diseases. [15] compared several machine learning algorithms, such as Decision Tree (DT), Naïve Bayes (NB), K-Nearest Neighbors (K-NN), and Neural Network (NN) on UCI Cleveland heart disease dataset. They concluded that DT had the highest accuracy of 89%.

The power of deep learning, pretrained networks can be used for feature extraction without having to re-train the whole network, transfer learning and classification. In this work, the trained networks Mobile Net are used to study their performance cardiovascular disease detection.

2. OBJECTIVE

Cardiovascular diseases (heart diseases) are the leading cause of death worldwide. The earlier they can be predicted and classified; the more lives can be saved. Electro-cardiogram (ECG) is a common, inexpensive, and noninvasive tool for measuring the electrical activity of the heart and is used to detect cardiovascular disease. In this work, the power of deep learning techniques was used to predict the four major cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes using the public ECG images dataset of cardiac patients.

2.1 PROBLEM STATEMENT

The mentioned methods were tested on the ECG Images dataset of cardiac patients [23]. This dataset contains 928 different patient records with four different classes as shown in Table II. These four classes are Normal person (NP), Abnormal Heartbeat (AH), Myocardial Infarction (MI), and History of Myocardial Infarction (H. MI). Fig. 6 depicts some samples from the dataset. A normal person is a healthy person who does not have any heart abnormalities. An abnormal heartbeat (arrhythmia) occurs when the electrical impulses in the heart become too fast, too slow, or irregular, so that the heart beats irregularly. Myocardial infarction, also known as heart attack, occurs when blood flow in the coronary artery of the heart decreases or stops, causing damage to the heart muscle. The patients with History of myocardial infarction who have recently recovered from myocardial infarction or heart attack

2.2EXISTING SYSTEM

Cardio-vascular diseases (CVD) is found to be rampant in the populace leading to fatal death. This paper compares and reports the various Classification, Data Mining, Machine Learning, Deep Learning models that are used for prediction of the Cardio-Vascular diseases. The survey is organized as threefold: Classification and Data Mining Techniques for CVD, Machine Learning Models for CVD and Deep Learning Models for CVD prediction. Data Set handled by the model and the number of attributes. According to research, if 102 cases are analyzed, SVM has a highest accuracy of 90.5% and Logistic Regression has the lowest of 73.9%. Survey of 1000 patients showed SVM with 92.1%.

Disadvantage of Existing System

- It does not execute very well when the data set has more sound i.e., target classes are overlapping.
- It doesn't perform well when we have large data set because the required training time is higher.

2.3 PROPOSED SYSTEM

The power of deep learning, pretrained networks can be used for feature extraction without having to re-train the whole network, transfer learning and classification. In this work, the Mobile Net are used as a transfer learning approach to study their performance in heart disease classification and as feature extraction for traditional machine learning methods for heart disease classification using ECG images and used for feature extraction of the ECG images. A Mobile Net Architecture is proposed for cardiovascular diseases prediction using lead-based ECG images. The proposed Mobile Net model achieves a success rate of 97.34%, outperforming the existing work

Advantages of Proposed System

- It has fewer parameters and higher classification accuracy.
- In order to further reduce the number of network parameters and improve the classification accuracy, dense blocks that are proposed in Dense Nets are introduced into Mobile Net.

3. RELATED WORKS

Many researches have been conducted for automatically predicting cardiovascular diseases using machine learning and deep learning methods by utilizing ECG as digitals or images data representation. Reference has compared machine learning and deep learning methods on UCI heart disease dataset to predict two classes. Deep learning method achieved the highest accuracy rate of 94.2%. In their architecture of deep learning model, they used three fully connected layers: the first layer consists of 128 neurons followed by a dropout layer with 0.2 rate, the second layer consists of 64 neurons followed by a dropout layer with 0.1 rate, and the third layer consists of 32 neurons. While the machine learning methods with features selection and outliers' detection achieved accuracy rates as: RF is 80.3%, LR is83.31%, K-NN is 84.86%, SVM is 83.29%, DT is 82.33%, and XGBoost is 71.4%. The research in concluded that deep Personal use is permitted, but republication/redistribution requires IEEE permission. See This article has been accepted for publication in a future issue of this journal, but has not been fully edited. Content may change prior to final publication. Citation information: Transactions on Artificial Intelligence learning has proven to be a more accurate and effective technology for a variety of medical problems such as prediction. And, deep learning methods will replace the traditional machine learning based on feature engineering. Kiranyaz et al.proposed a CNN that consisted of three layers of an adaptive implementation of 1D convolution layers. This network was trained on the MIT-BIH arrhythmia dataset to classify long ECG data stream. They achieved accuracy rates of 99% and 97.6% in classifying ventricular ectopic beats and supraventricular ectopic beats respectively. Also, the work in proposed a CNN that consisted of three 1D convolution layers, three max pooling layers and one fully connected layer and one softmax layer. The filter size for first and second convolutional layer was set to 5 and a stride of 2 was used the first two max pooling layers. They achieved an accuracy rate of 92.7% in classifying ECG heart beats using MIT-BIH arrhythmia dataset

4. METHODOLOGY OF PROJECT

A MobileNet architecture is proposed for cardiovascular diseases prediction using 12 lead-based ECG images. The proposed CNN model achieves a success rate of accuracy, outperforming the existing work and the state-of-the-art low-scale SqueezeNet and AlexNet, which achieved 95.10%, 95.47%, and 96.79%, respectively. To the best of our knowledge, this is the second study using the ECG images dataset of cardiac patients, which will encourage other researchers to explore other methods to detect cardiovascular diseases using this dataset.

MODULE DESCRIPTION

Data Collection:

In feature-based methods, various features of the website we have to collect the ECG images dataset. These features are then used to train deep learning models to detect cardiovascular diseases

Dataset:

In the first module, we developed the system to get the input dataset for the training and testing purpose. Dataset is given in the model folder. The dataset consists of 1377 ECG images.

Importing the necessary libraries:

We will be using Python language for this. First, we will import the necessary libraries such as keras for building the main model, sklearn for splitting the training and test data, PIL for converting the images into array of numbers and other libraries such as pandas, NumPy, matplotlib and TensorFlow.

Retrieving the images:

We will retrieve the images and their labels. Then resize the images to (224,224) as all images should have same size for recognition. Then convert the images into NumPy array

Splitting the dataset:

Split the dataset into train and test. 80% train data and 20% test data.

Building the model:

The concept of convolutional neural networks is very successful in image recognition. The key part to understand, which distinguishes CNN from traditional neural networks, is the convolution operation. Having an image at the input, CNN scans it many times to look for certain features and give the performance score depends on that score only predict
Person can have diseases or not.

Saving the Trained Model:

Once you're confident enough to take your trained and tested model into the production-ready environment, the first step is to save it into a.h5.

5. ALGORITHM USED IN PROJECT

MobileNet Architecture

As the name applied, the MobileNet model is designed to be used in mobile applications, and it is TensorFlow's first mobile computer vision model. MobileNet uses depth wise separable convolutions. It significantly reduces the number of parameters when compared to the network with regular convolutions with the same depth in the nets. This results in lightweight deep neural networks.
MobileNet is a class of CNN that was open-sourced by Google, and therefore, this gives us an excellent starting point for training our classifiers that are insanely small and insanely fast.

6. DATA FLOW DIAGRAM

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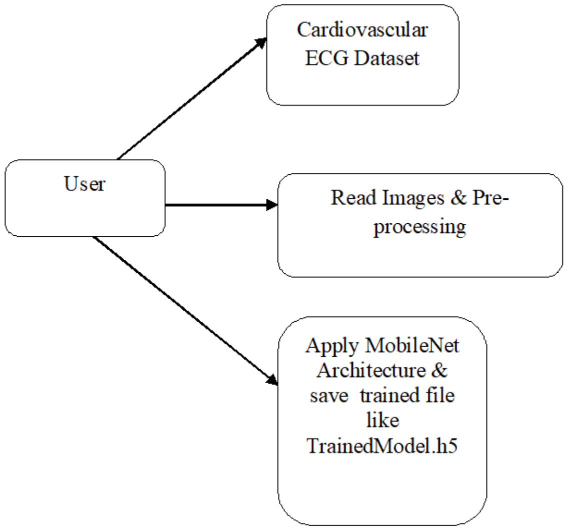
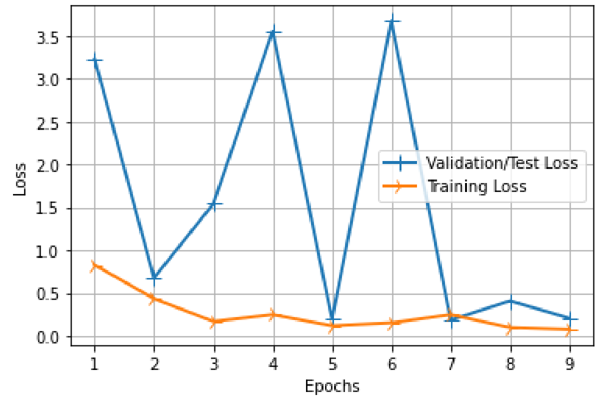
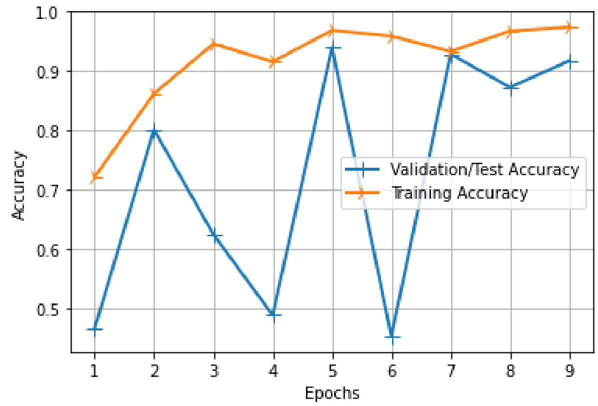


Fig:7 Flow Diagram





7.SYSTEM ARCHITECTURE

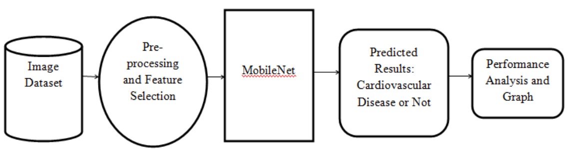


Fig:8 SYSTEM ARCHITECTURE OF PROJECT

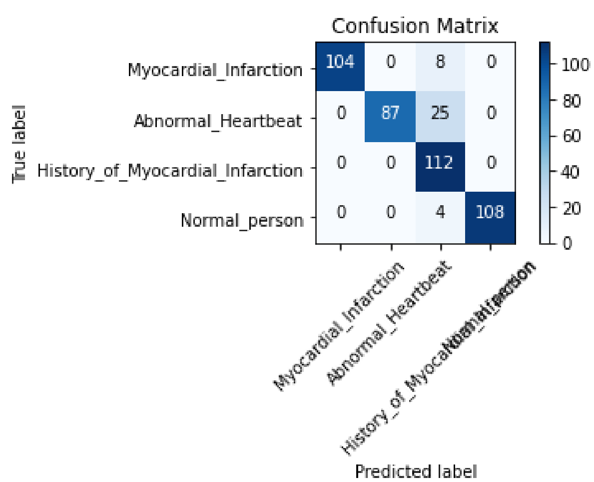
8. RESULTS

```
Model: "sequential"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 mobilenet_1.00_224 (Functio  (None, 7, 7, 1024)       3228864
 nal)

 global_average_pooling2d (G  (None, 1024)             0
 lobalAveragePooling2D)

 dense (Dense)               (None, 4)                 4100

=================================================================
Total params: 3,232,964
Trainable params: 3,211,076
Non-trainable params: 21,888
_________________________________________________________________
```



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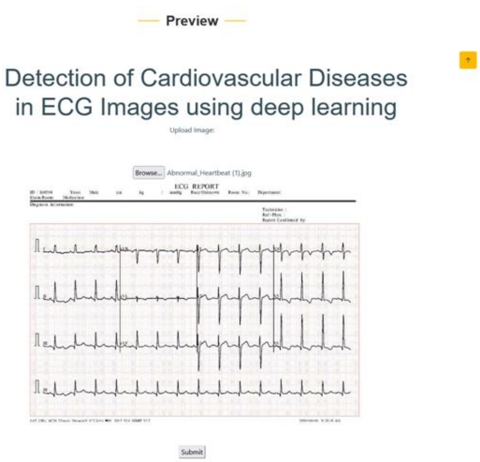

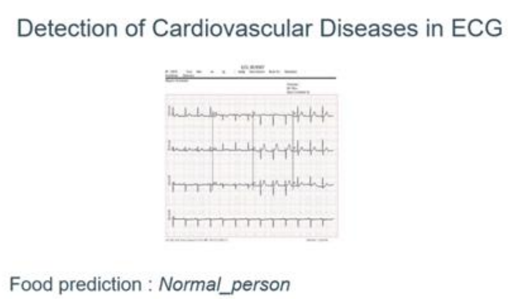

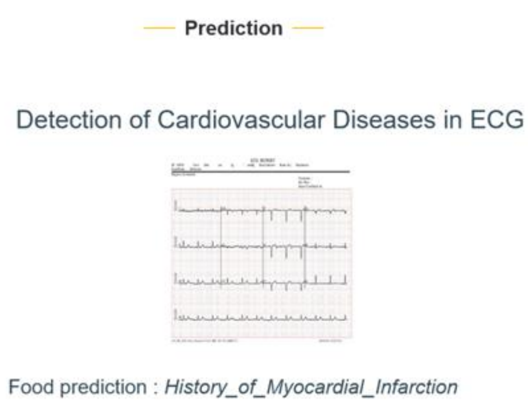

9. CONCLUSION AND FUTURE ENHANCEMENT

In future work, optimization techniques can be used to obtain optimized values for the hyperparameters of the proposed CNN model. The proposed model can also be used for predicting other types of problems. Since, the proposed model belongs to the family of low-scale deep learning methods in terms of the number of layers, parameters, and depth. Therefore, a study on using the proposed model in the Industrial Internet of Things (IIoT) domain for classification purposes can be explored.

In this study, we proposed a lightweight CNN-based model to classify the four major cardiac abnormalities: abnormal heartbeat, myocardial infarction, history of myocardial infarction, and normal person classes using public ECG images dataset of cardiac patients. According to the results of the experiments, the proposed MobileNet Architecture achieves remarkable results in cardiovascular disease classification and can also be used as a feature extraction tool for the traditional machine learning classifiers. Thus, the proposed CNN model can be used as an assistance tool for clinicians in the medical field to detect cardiac diseases from ECG images and bypass the manual process that leads to inaccurate and time-consuming results.

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