

ECG- Image Based Heartbeat Classification For Arrhythmia Detection Using IBM Watson Studio

ZEN SUNNY

MCA 950022

KRISTU JYOTI COLLEGE OF MANAGEMENT AND TECHNOLOGY

1.INTRODUCTION

1.1 Overview

According to the World Health Organization (WHO), cardiovascular diseases (CVDs) are the number one cause of death today. Over 17.7 million people died from CVDs in the year 2017 all over the world which is about 31% of all deaths, and over 75% of these deaths occur in low and middle-income countries. Arrhythmia is a representative type of CVD that refers to any irregular change from the normal heart rhythms. There are several types of arrhythmia including atrial fibrillation, premature contraction, ventricular fibrillation, and tachycardia. Although a single arrhythmia heartbeat may not have a serious impact on life, continuous arrhythmia beats can result in fatal circumstances.

2.2 Purpose

In this project, we build an effective electrocardiogram (ECG) arrhythmia classification method using a convolutional neural network (CNN), in which we classify ECG into seven categories, one being normal and the other six being different types of arrhythmia using deep two-dimensional CNN with grayscale ECG images. We are creating a web application where the user selects the image which is to be classified. The image is fed into the model that is trained and the cited class will be displayed on the webpage.

2.LITERATURE SURVEY

2.1 Existing Problem

Arrhythmia refers to an irregularity in the rate or rhythm of the heartbeat. This includes beating too fast or too slow or with an irregular rhythm. For instance, millions of people suffer from irregular heartbeats which can be lethal in some cases. Therefore, accurate and low-cost diagnosis of arrhythmic heartbeats is highly desirable.

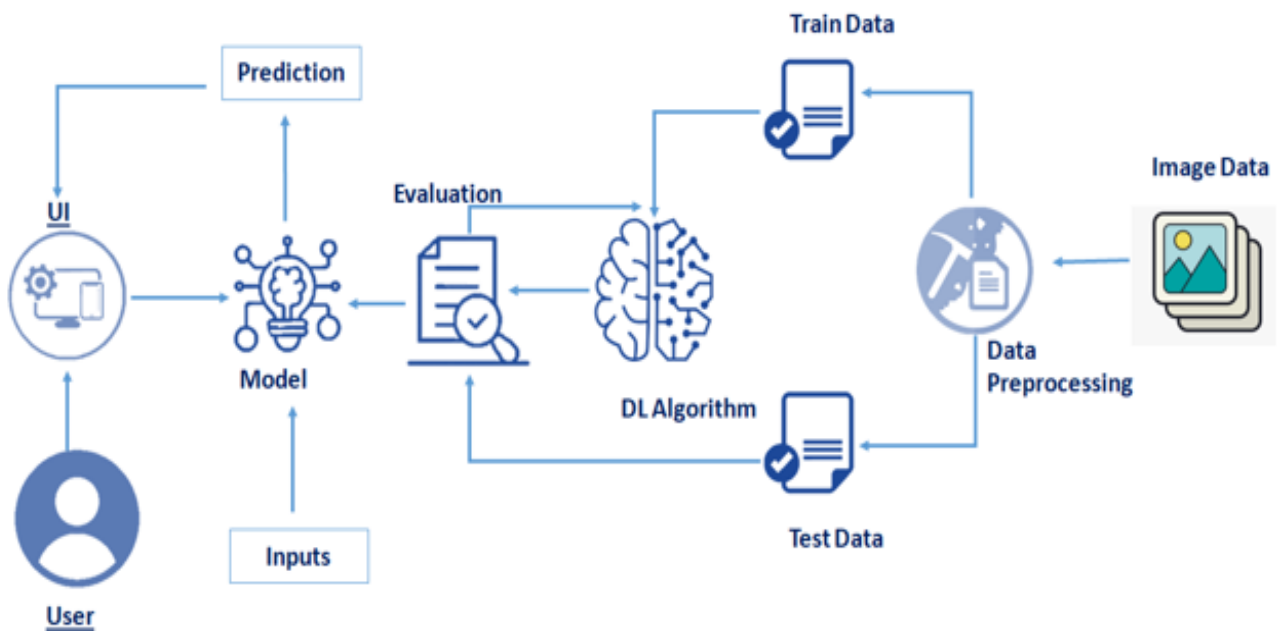
2.2 Proposed Solution

Many studies have developed arrhythmia classification approaches that use automatic analysis and diagnosis systems based on ECG signals. The most important factors for the analysis and diagnosis of cardiac diseases are features extraction and beats classification. Numerous techniques for classifying ECG signals were proposed in recent years and good results achieved. Deep learning models have proven useful and very efficient in the medical field to process scans, x-rays, and other medical data to output useful information. User interacts with User interface to upload image

- Uploaded image is analyzed by the model which is integrated
- Once model analyses the uploaded image, the prediction is showcased on the UI

3. THEORITICAL ANALYSIS

3.1 Block Diagram



3.2 Hardware / Software Designing

3.2.1 Hardware Requirements

- Processor: Minimum 1 GHz; Recommended 2GHz or more.
- Ethernet connection (LAN) OR a wireless adapter (Wi-Fi)
- Hard Drive: Minimum 32 GB; Recommended 64 GB or more.
- Memory (RAM): 4 GB and above.

3.2.2 Software Requirements

- Python
- Python Web Frameworks
- Anaconda Prompt
- Jupyter Notebook
- OpenCV
- ANN
- CNN
- Keras
- TensorFlow
- Flask

4.EXPERIMENTAL INVESTIGATIONS

Jupyter ECG (2) Last Checkpoint: 13 hours ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3

```
In [18]: model.compile(optimizer='adam',loss='categorical_crossentropy',metrics=['accuracy'])

In [36]: model.fit_generator(generator=x_train,steps_per_epoch = len(x_train),epochs=10,validation_data=x_test,validation_steps = len(x_test))

/opt/conda/envs/Python-3.8-main/lib/python3.8/site-packages/tensorflow/python/keras/engine/training.py:1839: UserWarning:
`Model.fit_generator` is deprecated and will be removed in a future version. Please use `Model.fit`, which supports generators.
warnings.warn("`Model.fit_generator` is deprecated and `

Epoch 1/10
480/480 [=====] - 68s 141ms/step - loss: 1.2177 - accuracy: 0.5586 - val_loss: 0.5235 - val_accuracy: 0.8377
Epoch 2/10
480/480 [=====] - 66s 138ms/step - loss: 0.2681 - accuracy: 0.9173 - val_loss: 0.4738 - val_accuracy: 0.8804
Epoch 3/10
480/480 [=====] - 66s 138ms/step - loss: 0.2127 - accuracy: 0.9379 - val_loss: 0.4131 - val_accuracy: 0.8769
Epoch 4/10
480/480 [=====] - 67s 139ms/step - loss: 0.1736 - accuracy: 0.9490 - val_loss: 0.3634 - val_accuracy: 0.8885
Epoch 5/10
480/480 [=====] - 67s 139ms/step - loss: 0.1562 - accuracy: 0.9553 - val_loss: 0.3720 - val_accuracy: 0.9011
Epoch 6/10
480/480 [=====] - 67s 139ms/step - loss: 0.1369 - accuracy: 0.9600 - val_loss: 0.3423 - val_accuracy: 0.9018
Epoch 7/10
```

Jupyter ECG (2) Last Checkpoint: 13 hours ago (autosaved) Logout

File Edit View Insert Cell Kernel Widgets Help Not Trusted Python 3

```
Epoch 7/10
480/480 [=====] - 67s 139ms/step - loss: 0.1431 - accuracy: 0.9558 - val_loss: 0.3327 - val_accuracy: 0.9160
Epoch 8/10
480/480 [=====] - 67s 140ms/step - loss: 0.1264 - accuracy: 0.9638 - val_loss: 0.3489 - val_accuracy: 0.9077
Epoch 9/10
480/480 [=====] - 66s 138ms/step - loss: 0.1071 - accuracy: 0.9666 - val_loss: 0.3397 - val_accuracy: 0.9071
Epoch 10/10
480/480 [=====] - 67s 139ms/step - loss: 0.1004 - accuracy: 0.9673 - val_loss: 0.3507 - val_accuracy: 0.9138

Out[36]: <tensorflow.python.keras.callbacks.History at 0x7f84f07de220>

In [37]: #save the model
model.save('ECG.h5')

In [38]: !tar -zcvf image-classification-model_new.tgz ECG.h5

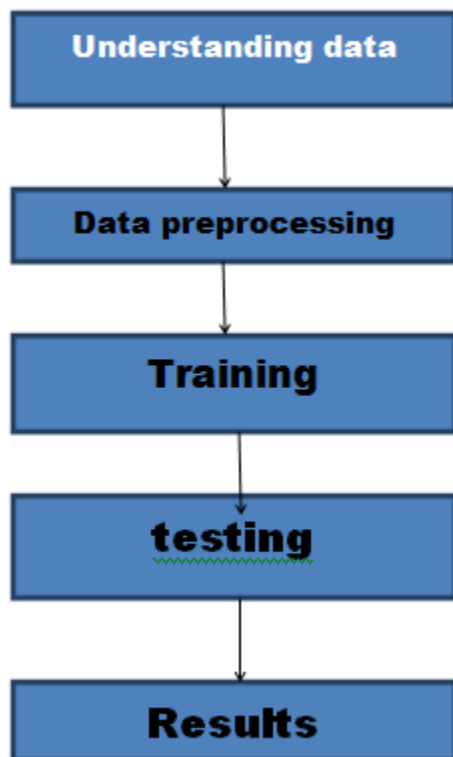
ECG.h5

In [39]: ls -l
dataset/
ECG.h5
image-classification-model_new.tgz
my_model.tar.gz
mymodel.tar.gz
```

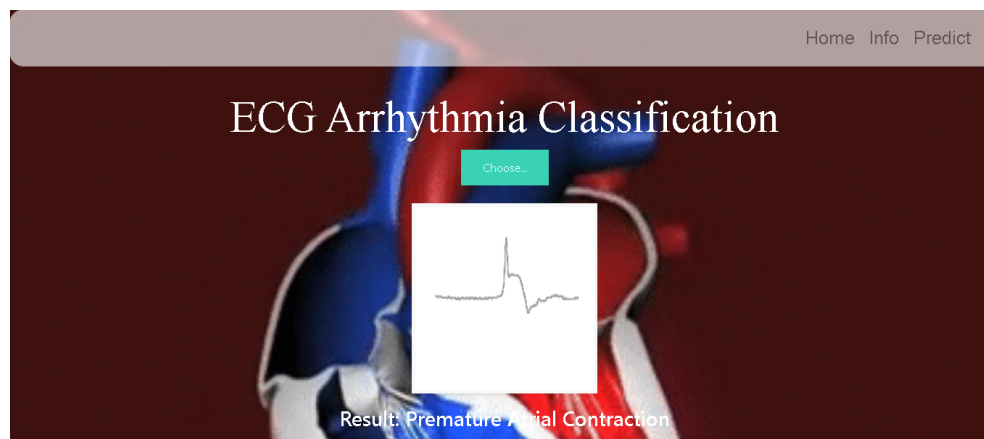
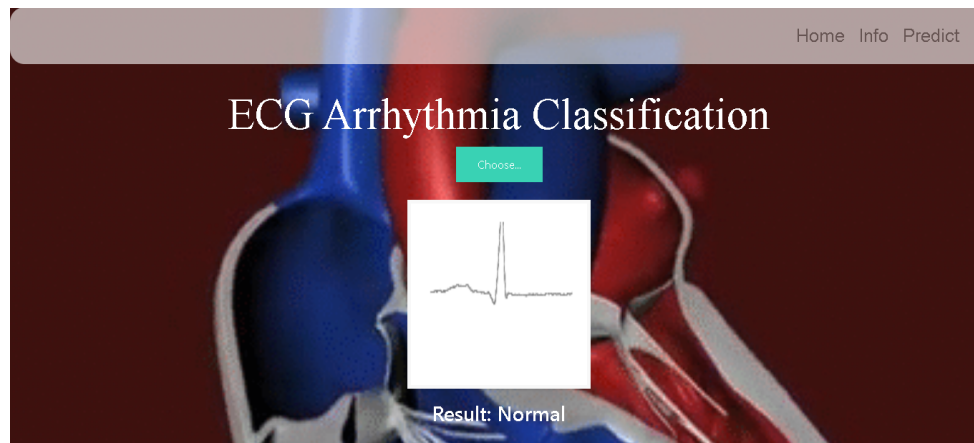
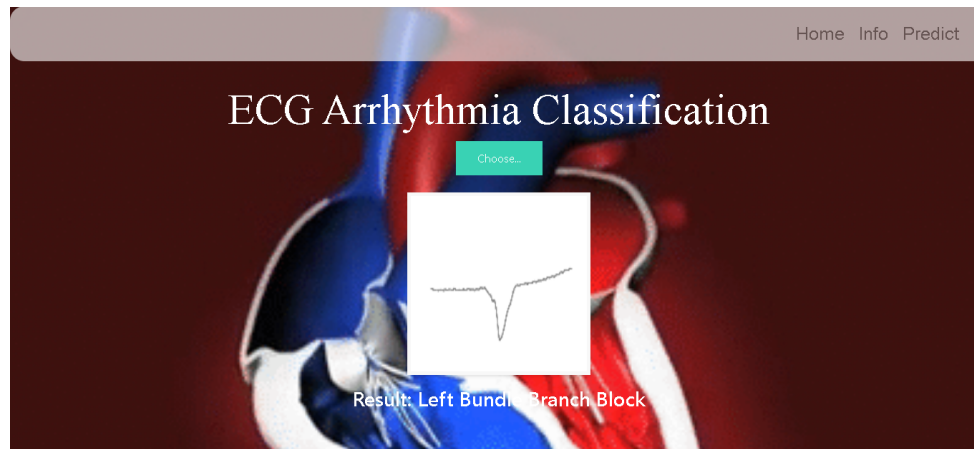
- **Data Collection.**
 - Collect the dataset or Create the dataset
- **Data Preprocessing.**
 - Import the ImageDataGenerator library
 - Configure ImageDataGenerator class
 - Apply ImageDataGenerator functionality to Trainset and Testset

- **Model Building**
 - Import the model building Libraries
 - Initializing the model
 - Adding Input Layer
 - Adding Hidden Layer
 - Adding Output Layer
 - Configure the Learning Process
 - Training and testing the model
 - Optimize the Model
 - Save the Model
- **Application Building**
 - Create an HTML file
 - Build Python Code

5.FLOWCHART



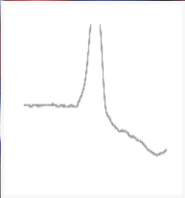
6.RESULT



Home Info Predict

ECG Arrhythmia Classification

Choose...



Result: Premature Ventricular Contractions

Home Info Predict

ECG Arrhythmia Classification

Choose...

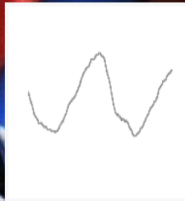


Result: Right Bundle Branch Block

Home Info Predict

ECG Arrhythmia Classification

Choose...



Result: Ventricular Fibrillation

7.ADVANTAGES AND DISADVANTAGES

ADVANTAGES

Automated ECG detection using deep learning models like CNNs could be very effective, cheap and scalable especially with the advent of transfer learning and pre-trained models which work quite well even with constraints like less data.

It reduces images to a form which is easier to process without losing features which are critical. Image pre-processing required is much less compared to other algorithms.

Deep learning does not require the design of handcrafted features, which is of its biggest advantages.

DISADVANTAGES

There has been a lot of fine-tuning of these methods to make them perform better for ECG images, and more so for the image analysis methods than for machine learning.

Despite the large number of publications, the performance numbers that have been published are very unsatisfying from a clinician's point of view.

It requires a large training data.

It requires appropriate model.

8.APPLICATIONS

There has been a lot of fine-tuning of these methods to make them perform better for ECG images, and more so for the image analysis methods than for machine learning.

There is certainly the potential that some of these methods gain importance in ECG. particular for image preprocessing and for detecting the images and predict the results. Working on this project leads us to believe that this work can play a part toward building a fully automated system for ECG image detection which may be useful for medical assistance.

The same methods used in this project can help in medical science, by making more models to work for many other diseases diagnoses. With this, medical technology can grow faster and be able to build 3D models that can predict accurately.

The increasingly growing number of applications of machine learning in healthcare allow us to glimpse at a future where data, analysis, and innovation work hand-in-hand to help countless patients without them even realizing it. Soon, it will be quite common to find ML-based applications embedded with real-time patient data available from different healthcare systems in multiple countries, thereby increasing the efficiency of new treatment options which were unavailable before.

9.CONCLUSION

In summary, This work has validated an ability to classify heartbeats. Classification process is using some features of heartbeats and machine learning classification algorithms with local host pc working using only one node, which are crucial for diagnosis of cardiac arrhythmia. The developed of these models can classify different ECG heartbeat types and thus, can be implemented into a CAD ECG system to perform a quick and reliable diagnosis. The proposed model has the potential to be introduced into clinical settings as a helpful tool to aid the cardiologists in the reading of ECG heartbeat signals and to understand more about them. The occurrence, sequential patterns and persistence of the classes of ECG heartbeats considered in this work can be grouped under six main categories which represents normal, PVC, PAC, and other. As a future work, implemented methods can be rebuilt to work with many classes the work can be developed to be used in real time and be trained continuously to enhance it and increase its accuracy. Moreover, the whole process of classification can be used with other types of datasets such as stress and clinical datasets

10.FUTURE SCOPE

In this project, we have designed & developed a deep learning model based on a convolutional neural network (CNN) which automatically classifies and predict the ECG images to desired output.

Deep learning is the latest trend in machine learning, which has already boost the performance in many nonmedical areas. Deep learning typically requires large training sets. This is the reason why medical applications have been the last applications to adopt deep learning, as annotated training images are significantly harder to obtain because of expert knowledge requirements and privacy concerns. But through machine learning , there can be a drastic improvement in the Medical field , which will inturn help the world grow . In many cases, it will also enable early discovery and treatment accessibility in remote or developing places, as ML can significantly reduce costs and necessity for doctor appointments.

Overall, ML in healthcare is an incredible development that will increase efficiency and accuracy in disease detection.

11.BIBLIOGRAPHY

Smartinternz.com

- 1.Li H, Yuan D, Ma X, Cui D, Cao L. Genetic algorithm for the optimization of features and neural networks in ECG signals classification. Sci Rep. 2017;7:41011.
- 2.Kachuee M, Fazeli S, Sarrafzadeh M. ECG heartbeat classification: a deep transferable representation. In: 2018 IEEE international conference on healthcare informatics (ICHI). New York: IEEE; 2018. p. 443–4.
- 3.Zhao Z, Yang L, Chen D, Luo Y. A human ECG identification system based on ensemble empirical mode decomposition. Sensors. 2013;13(5):6832–64.

- 4.Valenza G, Citi L, Lanatá A, Scilingo EP, Barbieri R. Revealing real-time emotional responses: a personalized assessment based on heartbeat dynamics. *Sci Rep*. 2014;4:4998.
- 5.Valenza G, Greco A, Citi L, Bianchi M, Barbieri R, Scilingo E. Inhomogeneous point-processes to instantaneously assess affective haptic perception through heartbeat dynamics information. *Sci Rep*. 2016;6:28567.
- 6.Christov I, Jekova I, Bortolan G. Premature ventricular contraction classification by the kth nearest-neighbours rule. *Physiol Meas*. 2005;26(1):123.
- 7.Sannino G, De Pietro G. A deep learning approach for ECG-based heartbeat classification for arrhythmia detection. *Fut Gener Comput Syst*. 2018;86:446–55.
- 8.Celesti F, Celesti A, Carnevale L, Galletta A, Campo S, Romano A, Bramanti P, Villari M. Big data analytics in genomics: the point on deep learning solutions. In: 2017 IEEE symposium on computers and communications (ISCC). New York: IEEE; 2017. p. 306–9.
- 9.Ahmad AK, Jafar A, Aljoumaa K. Customer churn prediction in telecom using machine learning in big data platform. *J Big Data*. 2019;6(1):28.
- 10.Ma'sum M.A, Jatmiko W, Suhartanto H. Enhanced tele ECG system using hadoop framework to deal with big data processing. In: 2016 international workshop on Big Data and information security (IWBIS). New York: IEEE; 2016. p. 121–6.

