ARRHYTHMIA DETECTION

Neural Networks Project

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1. Introduction

In the last years World Health Organization classified the Cardiovascular diseases (CVDs) as being the number 1 cause of death globally with over 17.9 million people that died in 2019. The death causes in CVDs are mostly due to heart attacks and strokes and one third of these occur prematurely in people under 70 years old [1].

A common type of CVD is arrhythmia which is a problem with the rhythm of the heartbeat, that can go too fast, too slowly or irregularly. The most common way to diagnose an arrhythmia is through an electrocardiogram (EKG or ECG). The ECG is a non-invasive medical tool that displays the rhythm and status of the heart by recording the electrical activity of the heart through small electrode patches attached to the skin of the chest, arms, and legs. A doctor needs to diagnose the results so it is an important task if automatic detection of irregular heart signals were possible. Therefore, the widely available digital ECG data and presents a good way to improve the accuracy and scalability of automated ECG analysis.

2. Related Work

In their paper published in Nature Medicine in 2019, Hannun et al [2] presented their work on developing a deep neural network (DNN) that classifies 12 rhythm categories using 91,232 single-lead ECGs from 53,549 patients. The *F1 Score*[1], which is a measure for tests' accuracy, obtained by them was for 0.837 for DNN, which exceeded the value 0.780 obtained by cardiologists. They have also demonstrated the generalizability of the DNN on the 2017 PhysioNet Challenge data[2] which contained four rhythm classes: sinus rhythm; atrial fibrillation; noise; and other. The class average F1 obtained was 0.83, among the best in the competition.

Isin et al [3] implemented a deep learning technique for classifying three different conditions of ECG waveform from MIT-BIH arrhythmia database [4]. The proposed system can distinguish and classify cardiac arrhythmias known as Right Bundle Branch Blocks (RBBB) from Paced Beats and Normal (Healthy) Beats. The highest obtained correct recognition rate was 98.51% while the testing accuracy was 92%.

A way of classifying more arrhythmia classes is presented in Yıldırım et al [5] where they use a deep learning approach for detecting 17 cardiac arrhythmia classes based on long-duration ECG signal analysis. The dataset used contains 1000 ECG signal fragments from the MIT-BIH Arrhythmia database for one lead (MLII) from 45 persons. They have designed a 1D-Convolutional Neural Network model (1D-CNN) that achieved a recognition overall accuracy of 17 cardiac arrhythmia disorders at a level of 91.33% and classification time per single sample of 0.015 sec.

[1] https://en.wikipedia.org/wiki/F1_score
[2] https://physionet.org/challenge/2017/

3. Database

The MIT-BIH Arrhythmia Database contains **48** half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89 years. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings and the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

The recordings were digitized at 360 samples per second per channel with 11-bit resolution over a 10 mV range. Two or more cardiologists independently annotated each record; disagreements were resolved to obtain the computer-readable reference annotations for each beat (approximately 110,000 annotations in all) included with the database.

Each record consists of 4 files with the following extensions:

- *.atr*: Atari 8-bit disk image that can be single or double density, containing 720 or 1440 sectors respectively
- *.dat*: binary file data that contains information about the application that created it
- *.hea*: a PhysioBank[3] header file
- *.xws*: image in the Xara Web Designer format

The arrhythmia recordings can be visualized with LightWAVE[4] which is a waveform viewer:

Fig. 1: Record 100 from MIT-BIH DB visualized using LightWAVE

[3] https://archive.physionet.org/physiobank/
[4] https://physionet.org/lightwave/?db=mitdb/1.0.0

4. Proposed Solution

We use Python and Keras open source library to create the 2 different CNN models that will analyze the visual records from the MIT-BIH DB. The first solution is a 1D CNN that collects all the high peaks of the heart beat signals and matches each one of the peaks to a sliced 256-sized sample about a peak. Then, this 256-sized sample is well-fitted into the model without flattening layer. The 5 signal names that are used as features are: MLII, V1, V2, V4 and V5.

The second solution uses a 2D CNN with 7 convolution layers and checks for 8 types of anomalies on the MIT-BIH DB data that was previously transformed into grayscale images.

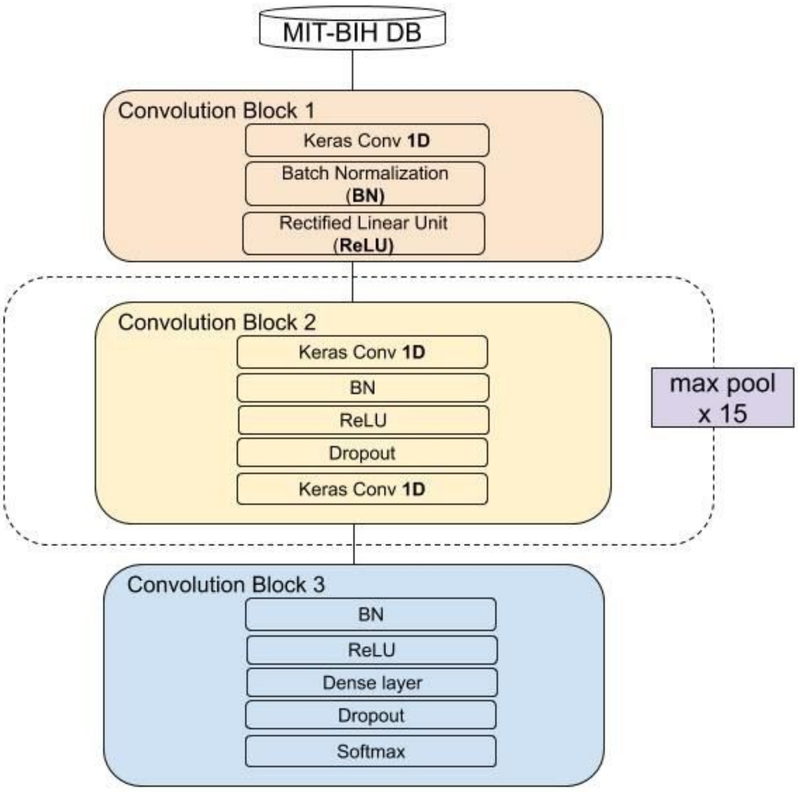
The source code of our solution is available on GitHub:
https://github.com/iantal/arrhythmia-detection

5. Project Implementation

5.1. 1D CNN

The periodic pattern of the heartbeat got us into trying to train on the signal data one 1D CNN model. The model consists of the following blocks:

- Input and a Residual Neural Network (ResNet) block
- A ResNet loop-back block
- Output block



The test set was composed of 8 records from the DB (having the IDs: 101, 105, 114, 118. 124. 201, 210, 217). The classes that were used for classification are:

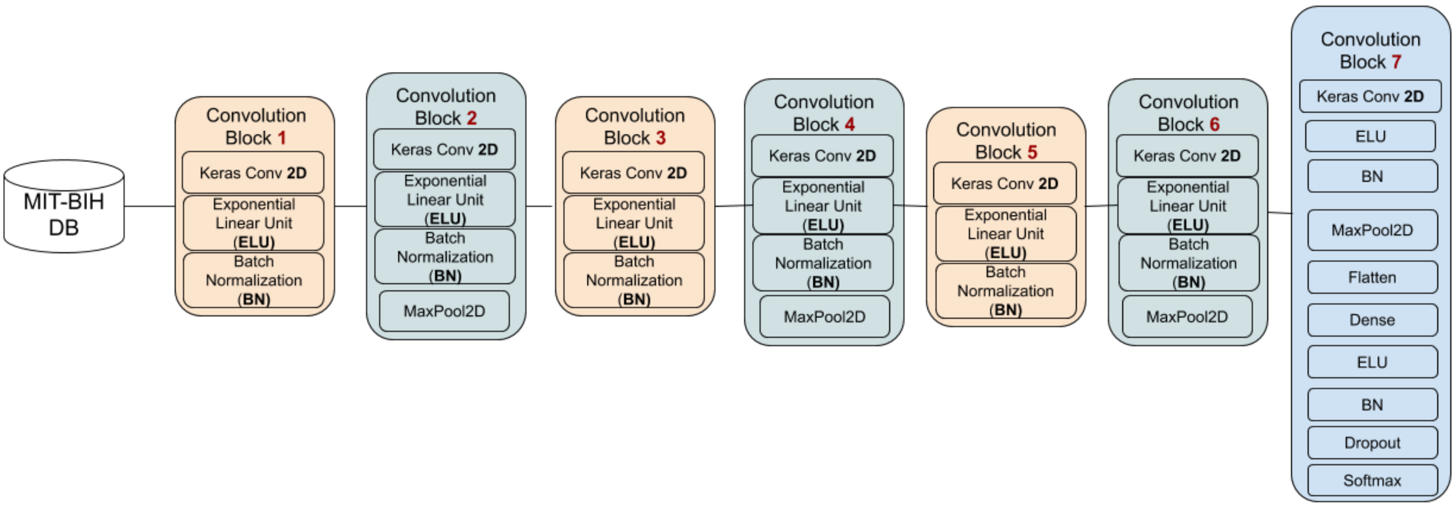
- **N** = normal beat
- **V** = premature ventricular contraction
- / = paced beat
- **A** = atrial premature beat
- **F** = fusion of ventricular and normal beat
- ~ = change in signal quality (non-beat)

The training data used was the 2017 Physionet challenge set from the CSV file.

5.2. 2D CNN

Steps taken:

- Download the MIT-BIH DB
- Create indexes for all the 48 records
- The signal records are transformed into 2D grayscale images - PNG files
- Index the 8 classes of symbols used in plots that will be considered during classification:
    - N = normal beat
    - L = Left bundle branch block beat
    - R = Right bundle branch block beat
    - A = Atrial premature beat
    - V = Premature ventricular contraction
    - / = Paced beat
    - E = Ventricular escape beat
    - ! = Ventricular flutter wave
- Prepare the dataset which is imbalanced by artificially augmenting smaller classes
- Create the CNN with the following training parameters:
    - IMAGE_SIZE = 128
    - BATCH_SIZE = 16
    - STEPS_PER_EPOCH = 50
    - EPOCHS = 100
- Build a Keras **sequential** model with 7 convolution layers with the architecture below:



References

[1] World Health Organization (2019). Cardiovascular diseases (CVDs). https://www.who.int/health-topics/cardiovascular-diseases/#tab=tab_1 Accessed 16 Feb 2020

[2] Hannun, A. Y., Rajpurkar, P., Haghpanahi, M., Tison, G. H., Bourn, C., Turakhia, M. P., & Ng, A. Y. (2019). Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network. *Nature Medicine*, 25(1), 65–69. doi:10.1038/s41591-018-0268-3

[3] Isin, A., & Ozdalili, S. (2017). Cardiac arrhythmia detection using deep learning. *Procedia Computer Science*, 120, 268–275. doi:10.1016/j.procs.2017.11.238

[4] MIT-BIH ECG database. https://physionet.org/content/mitdb/1.0.0/ Accessed 16 Feb 2020

[5] Yıldırım, Ö., Pławiak, P., Tan, R.-S., & Acharya, U. R. (2018). Arrhythmia detection using deep convolutional neural network with long duration ECG signals. *Computers in Biology and Medicine*. doi:10.1016/j.compbiomed.2018.09.009