

Heartbeat Classification and Arrhythmia Detection using Deep Learning.

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Abstract: As per the reports of the World Health Organization (WHO), the number one cause of death today is cardiovascular diseases (CVDs). As per their statistics, the number of deaths caused by CVDs is roughly 30%. Cardiac Arrhythmia is a condition in which the electrical activity of the heart is abnormal. The electrical activity is very irregular leading to the disruption in the cardiac rhythm. In this work, we propose an efficient arrhythmia classification model by leveraging a 2-D Convolutional Neural Network (CNN). This work is based on the optimization of CNN using various techniques like batch normalization, data augmentation etc. This approach is unsupervised learning-based approach i.e. we have bypassed the conventional data pre-processing, feature extraction etc. and yet we achieve accuracy closer to 90% and more or less the same level of sensitivity. We also propose a method to classify the heartbeats which helps in classification of 5 different categories of arrhythmia which is compliant to the AAMI EC57 standards. This approach is based on t-sne model and we have been able to achieve an average accuracy closer to 93%.

Keywords: ECG, Arrhythmia, CNN, deep learning, t-sne

1. Introduction

Heart, is fundamentally electrical in nature. ECG is one of the most commonly used instruments to detect any abnormalities in the electrical function of heart. The irregularities in the electrical activity is called arrhythmia. There are several types of arrhythmia viz. premature contraction, ventricular fibrillation, tachycardia etc. Interpretation of ECG takes a lot of practice and is indeed a difficult skill to acquire and is also very time-consuming.

Also, ECG data is very complex owing to different waveforms and their interpretation. With the advent of different computational paradigms, researchers have been very curious to explore the possibilities of leveraging different techniques like Machine Learning (ML), deep learning (DL) etc. to interpret the ECG like a cardiologist. It is very important to note that the accuracy if diagnosis is very critical as any deviation could be fatal.

Many approaches have been proposed so far from feed-forward neural networks to fuzzy networks and wavelet transform. Linh et al [1] has proposed a fuzzy neural network and performed feature extraction applying Hermite function. Guler et al [2] proposed a feed-forward neural network based approach and applied Wavelet Transforms for feature extraction. Ubeyli [3] proposed recurrent neural networks (RNN) classifier and he employed Eigen vector approach for feature extraction.

Many researchers have tried to address this concern and proposed different machine learning techniques with special focus on improving the accuracy in detecting the different waveforms [4-5]. Most of these are conventional approaches which employ conventional data pre-processing techniques typically involved in supervised learning problems. The data then undergoes the feature extraction and is used in the subsequent steps leading to classification.

Other conventional approaches employ machine learning approaches like SVM, PCA etc. [6-8]. Though the feature extracted by the machine learning algorithms are accurate and scalable but the deep learning frameworks go one step ahead and lets the agent learn the features [9-11]. The deep learning framework lets the agent / machine learn from the data and detect patterns which gives more accurate analysis of ECG that can be compared to that of a manual inference by a cardiologist [12]. On the downside, these frameworks require very huge amount of training data and large number of variables.

Most conventional algorithms have some downsides that include a) achieving better performance without cross-validation, b) losing the beats due to filtering and feature extraction c) less number of arrhythmia type classification d) low accuracy and performance.

In this work we propose a novel deep learning based framework to analyze the complex ECG data and develop a transferable representation of ECG signals. It is important to know that to realize such a framework it is very important to describe an architecture that offers scope for learning the signal representation. Once we build a model and train that model on a huge training data set, the model will be able to learn from the pattern and also allow using that representation to transfer the knowledge.

Also, the proposed algorithm employs a 2-D CNN with monochrome images of the ECG. One of the advantages of our approach is that conventional data pre-processing steps like feature extraction and noise removal and filtering are not required as the algorithm converts the 1-D Signal data to a 2-D image. Additionally, to improve the accuracy of the model we can augment the 2-D images and increase the size of the training data. Since our algorithm transforms a 1D signal to a 2D image, the model will automatically ignore the noise and extract the feature map. This allows the proposed model to be employed on heterogeneous signals and devices with different feature sets like sampling rate, amplitude etc. unlike the conventional models that require the data from a homogeneous set of instruments and feature sets which makes this model a potential candidate to be employed in a clinical setup.

2. Methodology

2.1 1-D signal to 2-D Transformation method:

In this approach we follow the general steps as shown in figure 1

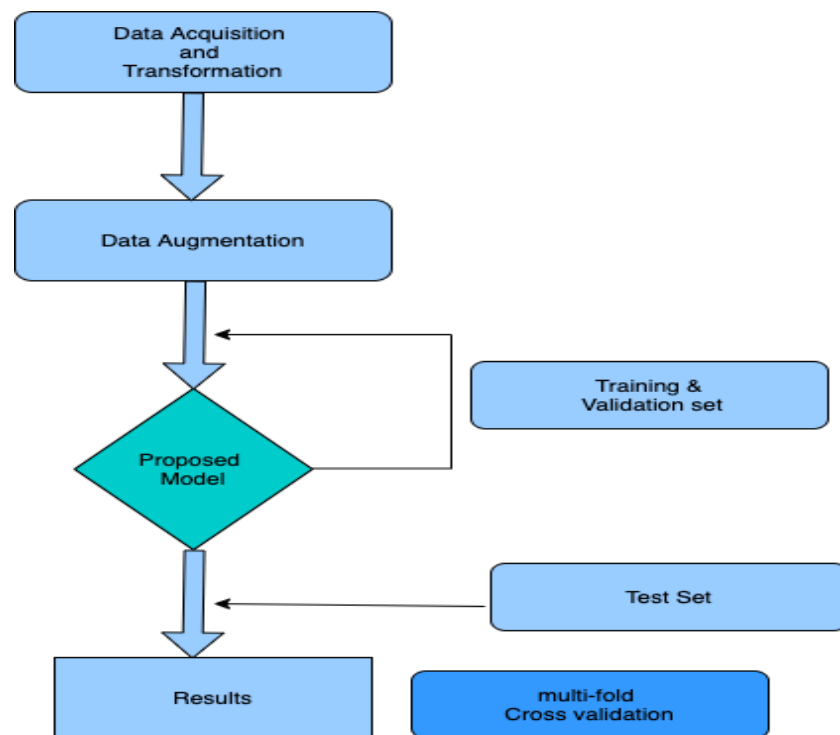


Figure 1. Overall Process used in arrhythmia classification

We start with acquiring the ECG data and then transforming the data to a 2D image which is then augmented to increase the size of the training set data. This data is then fed to the model discussed in this paper.

As mentioned we are transforming a 1-D signal data to a 2-D image (grayscale) as CNN requires image data. We realize this by plotting every beat as a matrix of 128 x 128 image which is sliced based on the Q-wave peak time. Since we are slicing at Q-wave, we can now define a beat by considering this peak as the mean peak discounting the 1st and last 20 cycles from the previous and the subsequent peaks. Thus, we can define the beat range as:

$$T(Qpeak(n - 1) + 20) \leq T(n) \leq T(Qpeak(n + 1) - 20) \quad (1)$$

Figure 2, shown below shows each of the 8 types of ECG beats, i.e. 1 normal beat and 7 arrhythmic beats obtained by creating a 128 x 128 matrix.

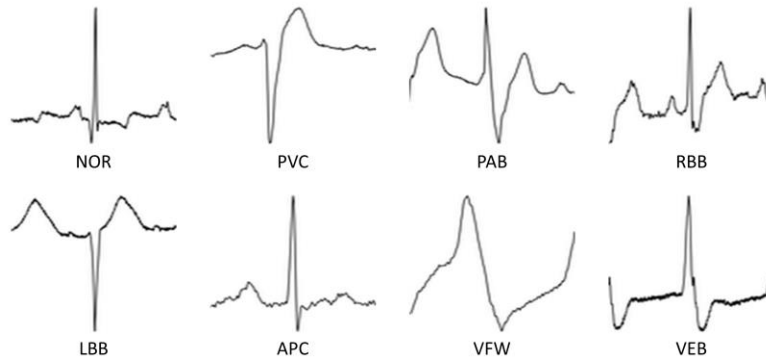


Figure 2. Normal and 7 Arrhythmia beats

In our work as aforementioned, we have leveraged CNN as described by LeCun et al. [13]. Since we are using the 128 x 128 matrix as images which exponentially increase the number of parameters and hence the conventional feed-forward network cannot be used as it will not prove to be efficient. Since we are using a 128 X 128 matrix representation of the ECG beats we can extract the correlation of the spatially adjacent pixels. This helps in an efficient feature extraction of the local features and the augmentation of 2D pooling layers prove to be more efficient in the feature extraction.

Figure 3, shows the general architecture of the proposed model

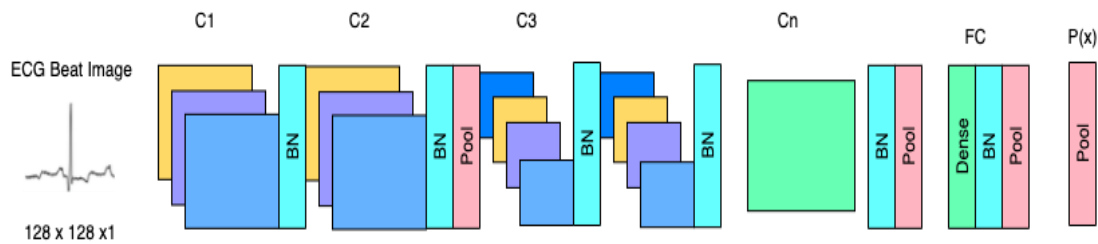


Figure 3. Proposed Model

The data augmentation will help in reducing the issue of over-fitting and balance the class distribution and this can have a significant impact in such use cases as the medical data is highly unstructured and also the ratio of normal and abnormal cases is too high.

The downside of using such algorithms which uses a gradient descent is that the model may not converge or might fall into a local minima and it is characterized by the learning rate. One of the common ways to ensure that the model converges is to make sure that we set an intelligent initialization of weights which are represented as kernels and a group of which forms a single convolution layer.

The weights that are initialized are random in nature and the range of such weights can be defined as:

$$x = \frac{\sqrt{n}}{In+Out} ; [-x, x] \quad (2)$$

Where , ‘n’ is the number of convolutional layers and In and Out are number of input and output units at the kernel weights respectively.

2.2 Using Transfer Learning Method

In this method we try to develop a framework that represents signal in a transferable format. This can be used to transfer the learning between different tasks. To realize this it becomes imperative for the neural network used to offer high capacity for learning the transferable representation. We have trained our proposed model on the arrhythmia data and hence we anticipate that the learning might have happened based on the patterns, mostly spatial in nature that the model might have learnt.

In our work we consider the following mapping which is in alignment with AAMI EC57 [14]:

- a) N : Normal
- b) S : Atrial ,Aberrant atrial, Nodal and Supra-ventricular premature
- c) V: Premature ventricular contraction and ventricular escape
- d) F: Combination of normal and ventricular.
- e) Q: Unclassifiable

Pre-processing:

Figure 4, shows a sample of 10 second window of the ECG Data.

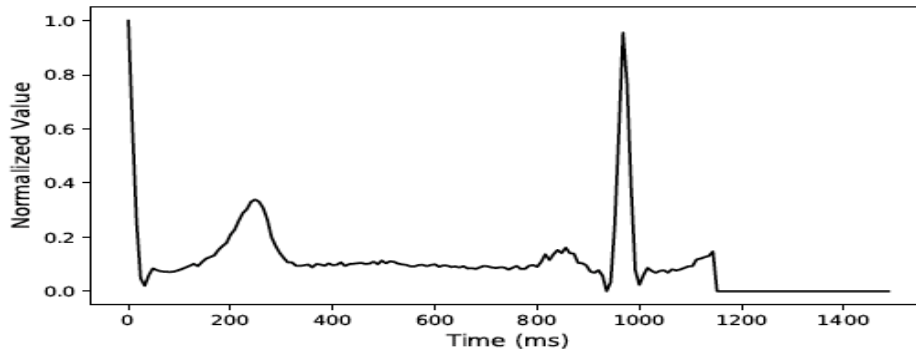


Figure 4. sample 10s ECG Window

Here's how we extracted the beats from the signal.

- a. Splitting the ECG data into 10s window
- b. Normalize the amplitude
- c. Determine the set of local maxima
- d. Find ECG R-Peak candidates
- e. Determine the median of R-R time intervals
- f. For each peak R, select a corresponding signal part whose length is equal to 1.2T
- g. Padding

Figure 5 below, shows the general architecture of the proposed work. Each convolutional layer apply 1-D convolution and has 32 kernels each of size 5. The prediction network has 5 residual blocks followed by 2 fully-connected layers. Each fully-connected layer consists of 32 neurons and uses a Softmax to predict. Each residual block has 2 convolutional layer and 2 ReLU activators [t-sne 19] and skip connection [15].

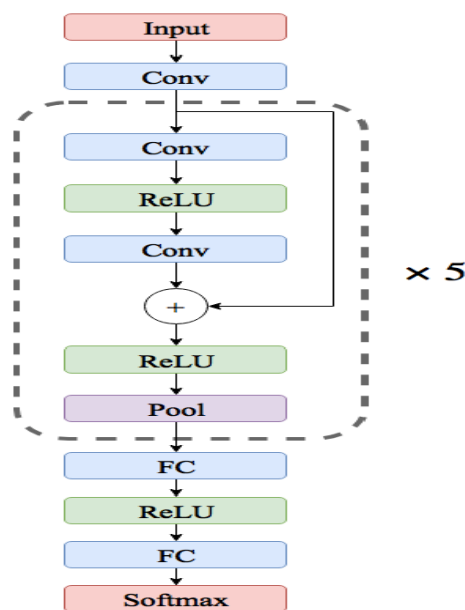


Figure 5. Architecture of proposed algorithm

In our experiments we have leveraged the Tensor Flow library [16] for modeling and evaluation. As aforementioned we have used gradient descent whose learning rate is decayed exponentially at a rate of 0.75 per 10000 iterations.

3. Results and Discussion

When we started experimenting with the dataset we realized that the data was quite imbalanced as shown in Figure 6 and after employing the resampling techniques we got a perfectly distributed data as shown in figure 7.

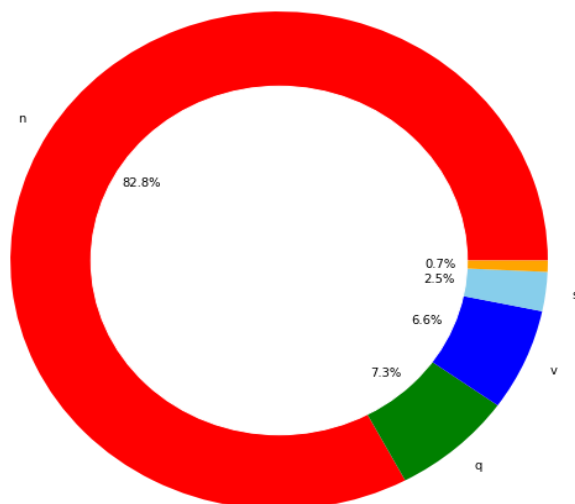


Figure 6. Imbalance in data

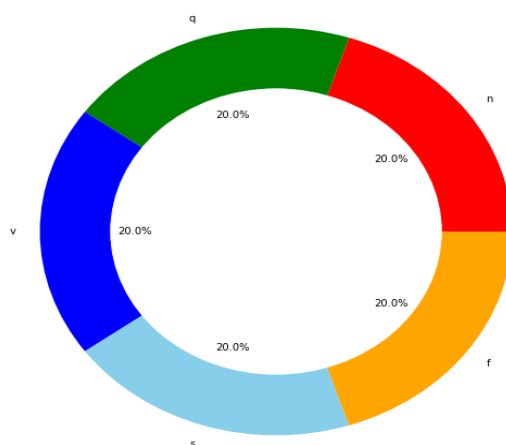


Figure 7. Balanced after resampling

Figure 8 as shown below, helps to visualize 1 ECG beat per category in the Time vs. Amplitude format. This shows how different arrhythmic beats have different waveforms and how much do they vary from the normal beats shown in blue color.

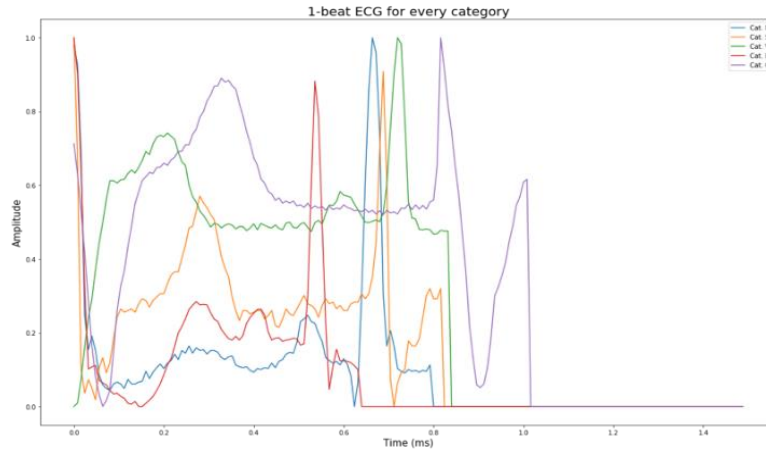


Figure 8. ECG beats visualization

Figure 9 represents different graphs of loss, AUC avg accuracy and ppv for each global step. Figure 10 shows the sensitivity values for each type of arrhythmic beat until the end of 10k epochs. We can notice that the loss starts converging almost near to 1k epochs unlike other metrics.

This leads us to infer that the early stopping with loss will not lead to higher accuracy and sensitivity in cases where there is an imbalance between the positive and negative cases. Hence it is suggested to rely on other metrics like AUC or avg sensitivity with CNN.

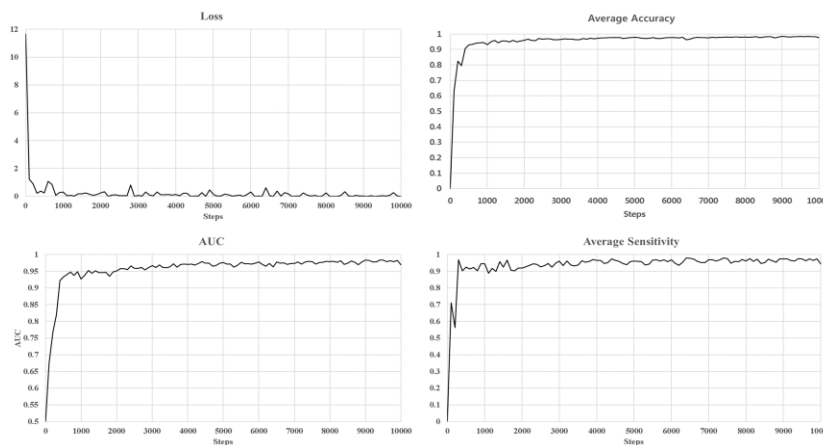


Figure 9. Evaluation Results of transformation method

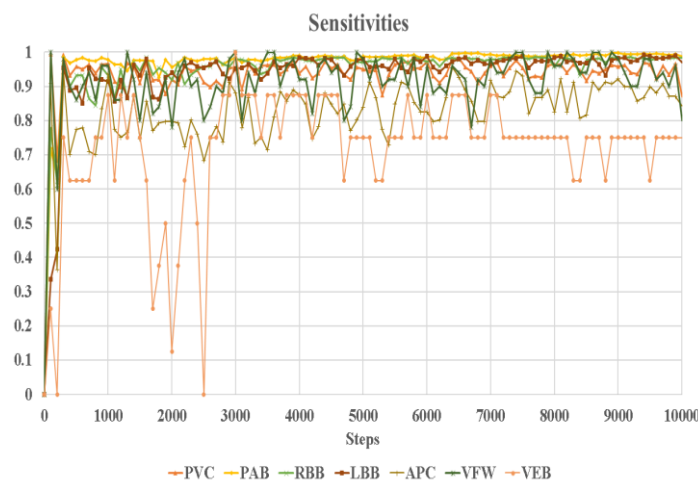


Figure 10. Sensitivity of each type predicted using transformation method

Figure 11, shows the results derived using the transformation method, where the 1-D signal data was transformed into 2-D 128 x 128 greyscale image. We have tested the classifier on 4,000 beats that we not a part of training data. Figure 12, shows the confusion matrix of the classifier on the test set and we can infer that the model is making accurate predictions and also distinguish various arrhythmia classes.

Figure 11 shows the avg accuracy of the proposed method. From the results we can infer that the proposed model has a very high accuracy and this has been characterized by the residual connections in the network which allows better learning in the networks compared to conventional methods.

mthyrV			mthyrS			mthyrF			mthyrQ		
precision	recall	f1	precision	recall	f1	precision	recall	f1	precision	recall	f1
0.98	0.88	0.92	0.95	0.88	0.91	1.00	1.00	1.00	0.99	0.92	0.95

Figure 11. Results of the transfer learning method

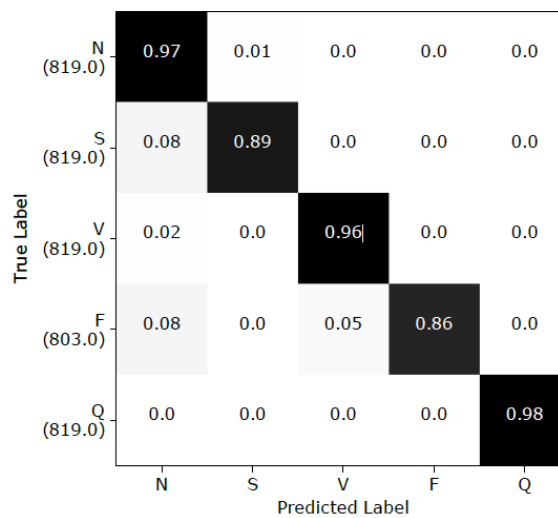


Figure 12. Confusion matrix (transformation method)

4. Conclusion

We have presented different experiments in our study to classify the different types / classes of arrhythmia based on different methods like transfer learning and transformation methods. We have trained our models using almost 10k ECG beats that includes normal and 7 arrhythmic beats. The optimized transformation based model achieved an avg accuracy of 99.05% while the transfer learning based method also achieves similar results.

From the results we can infer that the CNN can be employed in detecting and classifying the different classes of cardiac arrhythmia.

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