Cardiac Arrhythmia Detection from ECG with Convolutional Recurrent Neural Networks

Jérôme Van Zaen¹, Ricard Delgado-Gonzalo¹, Damien Ferrario¹, and Mathieu Lemay¹

Swiss Center for Electronics and Microtechnology (CSEM), Neuchâtel, Switzerland

Abstract. Except for a few specific types, cardiac arrhythmias are not immediately life-threatening. However, if not treated appropriately, they can cause serious complications. In particular, atrial fibrillation, which is characterized by fast and irregular heart beats, increases the risk of stroke. We propose three neural network architectures to detect abnormal rhythms from single-lead ECG signals. These architectures combine convolutional layers to extract high-level features pertinent for arrhythmia detection from sliding windows and recurrent layers to aggregate these features over signals of varying durations. We applied the neural networks to the dataset used for the challenge of Computing in Cardiology 2017 and a dataset built by joining three databases available on PhysioNet. Our architectures achieved an accuracy of 86.23% on the first dataset, similar to the winning entries of the challenge, and an accuracy of 92.02% on the second dataset.

Keywords: Cardiac arrhythmia · Machine learning · Neural networks · ECG.

1 Introduction

Irregular electrical conduction in cardiac tissue often causes heart arrhythmia. Atrial fibrillation is the most prevalent arrhythmia as it affects 1–2% of the population [1]. Its prevalence increases with age, from <0.5% at 40–50 years to 5–15% at 80 years. Despite not being a life-threatening condition from the start, it can lead to serious complications [14]. In particular, atrial fibrillation is associated with a 3–5 fold increased risk of stroke and a 2-fold increased risk of mortality [15]. It was also shown to be linked with a 3-fold risk of heart failure [28]. Heart palpitations, shortness of breath, and fainting are common symptoms. However, around one third of the cases are asymptomatic, which prevents early diagnosis. This, in turn, delays early treatment which might protect the patient from the consequences of atrial fibrillation and stop its progression. Indeed, atrial fibrillation causes electrical and structural remodeling of the atria which facilitates its further development, i.e. atrial fibrillation begets atrial fibrillation [29][21].

The 12-lead ECG is the gold standard to diagnose abnormal heart rhythms. A trained electrophysiologist can select the most appropriate therapy after reviewing ECG signals and the patient history. This is a time-consuming task,
especially for long recordings such as the ones collected with Holter monitors. Several approaches have been proposed to make this task easier and less time-consuming \[22,5\]. Indeed, even without perfect accuracy, these approaches are helpful to quickly select relevant ECG segments for in-depth analysis by a specialist.

Recently, neural networks have shown remarkable performance in numerous domains compared to other methods. In particular, image processing was the first field where deep neural networks surpassed existing approaches by a large margin \[14\]. Since then they have also been applied to multiple signal processing classification and regression tasks with time series as inputs. In particular, several neural networks have been proposed to detect and classify cardiac arrhythmia from ECG signals.

In the context of the challenge of Computing in Cardiology 2017 \[3\], a few approaches based on neural networks were proposed to classify single-lead ECG signals into one of the following classes: normal rhythm, atrial fibrillation, other rhythm, and noise. One of these approaches applies two-dimensional convolutional layers to spectrograms computed over sliding windows \[35\]. Aggregation of the features extracted from the spectrograms was done either with a simple averaging over time or a recurrent layer. However, due to convergence issues, convolutional and recurrent layers were trained separately. A similar approach used a 16-layer convolutional network to classify arrhythmia from ECG records \[32\]. Each layer includes batch normalization, ReLU activation, dropout, one-dimensional convolution, and global averaging.

Cardiologist-level arrhythmia detection was reached recently by a convolutional neural network \[24\]. This network with 34 layers was trained on a very large dataset of 64,121 single-lead ECG signals collected from 29,163 unique patients. It can detect 12 different types of cardiac arrhythmia, including atrial fibrillation, atrial flutter, and ventricular tachycardia. Another approach applied convolutional neural networks to time-frequency representations of ECG data in order to classify arrhythmia \[30\]. Two types of time-frequency representations were compared: the short-time Fourier transform and the stationary wavelet transform. In this study, the second transform led to a neural network yielding higher performance.

Thus, several neural network architectures achieved good classification performance for the detection of abnormal heart rhythms from ECG signals. These results are promising as they prefigure detection systems that will quickly process long ECG records to extract pertinent segments for further analysis by an electrophysiologist. Hopefully, this will reduce the time needed to achieve a diagnosis and thus to select the most appropriate therapy as early as possible. We recently proposed an approach to tackle this issue \[27\]. This approach combined a smart vest to record a single-lead ECG over long periods of time and a convolutional recurrent neural network to detect abnormal rhythms. In this paper, we consider variations of the neural network architecture proposed previously and apply them to two datasets for the classification of cardiac arrhythmia. This paper is structured as follows. First, the datasets of ECG data and the considered
neural network architectures are presented in Section 2. Then, the results are reported in Section 3 and discussed in Section 4. Finally, a brief conclusion ends this paper in Section 5.

2 Materials and Methods

2.1 Datasets

We trained neural networks to classify cardiac arrhythmia from ECG data with two datasets. The first one is the dataset used for the challenge of Computing in Cardiology 2017 [3]. It includes 8528 single-lead ECG signals recorded with an AlivCor device. The signals are sampled at 300 Hz with durations ranging from 9 to 60 seconds. Each record was acquired when the subject placed their hands on the two electrodes. This resulted in a lead I (left arm – right arm) ECG. However, many signals are inverted (right arm – left arm) as the device has no specific orientation.

All ECG records were labeled with one of the following four classes: normal sinus rhythm, atrial fibrillation, other rhythm, and noise. No additional information was available about the heart rhythms included in the other rhythm class. The class proportions are not balanced and vary from 3.27% for noise to 59.52% for normal sinus rhythm. For training and evaluation, we split the dataset into a training set with 6000 signals (70.4%), a validation set with 1264 signals (14.8%), and a test set with 1264 signals (14.8%) while approximately preserving class proportions. The full breakdown for each class and each subset is reported in Table 1.

Table 1. Breakdown of training, validation, and test sets for the dataset of the challenge of Computing in Cardiology 2017.

| Class            | Training | Validation | Test   |
|------------------|----------|------------|--------|
| Normal rhythm    | 3571 (59.5%) | 752 (59.5%) | 753 (59.6%) |
| Atrial fibrillation | 534 (8.9%) | 112 (8.9%) | 112 (8.9%) |
| Other rhythm     | 1699 (28.3%) | 358 (28.3%) | 358 (28.3%) |
| Noise            | 196 (3.3%) | 42 (3.3%) | 41 (3.2%) |
| Total            | 6000 (100%) | 1264 (100%) | 1264 (100%) |

The participants of the challenge of Computing in Cardiology 2017 were ranked according to the following score evaluated on a private test set [3]:

\[ S_{\text{CinC}} = \frac{F_{1n} + F_{1a} + F_{1o}}{3} \]  
(1)
where $F_{1n}$, $F_{1a}$, and $F_{1o}$ are the $F_1$ scores for normal rhythm, atrial fibrillation, and other rhythm. The four winners \textsuperscript{26,4,33,12} reached a score of 0.83. It is worth mentioning that the private test set used during the challenge was not released yet and thus could not be used for evaluation purposes.

A number of features make this dataset challenging for cardiac arrhythmia classification. First, as mentioned previously, many ECG signals are inverted since the recording device lacks a clear usage orientation. Second, the classes are not balanced. There are few records labeled atrial fibrillation and noise compared to the ones labeled normal rhythm and other rhythm. Third, the record durations are not identical but instead vary between 9 and 60 seconds. These variations are illustrated in Figure 1. Most ECG signals last around 30 seconds but a significant number have shorter or longer durations. Furthermore, labeling is relatively coarse as there is a single label for each ECG record. Using more than a single label would have been more appropriate as the cardiac rhythm seems to change over the course of the several signals. Finally, the signal quality of a non-negligible part of the records is quite poor. Four examples are shown in Figure 2 to illustrate some of these issues. The first two examples are labeled normal rhythm and atrial fibrillation and their overall quality is good. The third example is labeled normal rhythm and has good quality as well. However, it is inverted (R peaks are negative) compared to the first example. In this case, the device was mostly likely held in the wrong orientation. The last example is an example of atrial fibrillation with poor quality and very short duration. Indeed, the ECG signal is very noisy at the end and seems to miss some heartbeats. It also illustrates that the records do not share the same duration. This dataset will be referred to as the CinC 2017 dataset in the rest of the manuscript.

The second dataset we considered was built by combining three databases from PhysioNet \textsuperscript{8}: the MIT-BIH Atrial Fibrillation Database \textsuperscript{19}, the MIT-BIH Arrhythmia Database \textsuperscript{20}, and the Long-Term Atrial Fibrillation Database \textsuperscript{23}. The MIT-BIH Atrial Fibrillation Database includes 23 two-lead ECG records sampled at 250 Hz that last 10 hours. The MIT-BIH Arrhythmia Database is composed of 48 half-hour ECG records with two leads collected from 47 subjects. The signals were sampled at 360 Hz. The Long-Term Atrial Fibrillation Database includes 84 two-lead ECG records sampled at 128 Hz. These records were collected from subjects with paroxysmal or sustained atrial fibrillation and their durations varied but were typically between 24 and 25 hours. These three databases were annotated with several different cardiac rhythms: atrial bigeminy, atrial fibrillation, atrial flutter, ventricular bigeminy, heart block, idioventricular rhythm, normal rhythm, nodal rhythm, paced rhythm, pre-excitation, sinus bradycardia, supraventricular tachyarrhythmia, ventricular trigeminy, ventricular fibrillation, ventricular flutter, and ventricular tachycardia.

As the ECG records from these three databases were too long to use as inputs for neural networks, we extracted 30-second segments. Segments annotated with more than a single label were discarded to avoid errors due to the presence of multiple cardiac rhythms. Since the proportions of segments with normal rhythm and atrial fibrillation completely dominated the proportions for the other
rhythms, we combined them in a single class labeled as *other rhythm*. Furthermore, each segment resulted in two 30-second signals since two ECG leads were recorded in the three databases. The main reason for keeping both leads was to test if a neural network could learn to take into account ECG signals with different morphologies for the task of arrhythmia detection.

The extracted 30-second ECG signals from the three databases were split into training, validation, and test sets. We applied an iterative procedure to assign subjects to these subsets while targeting a 60%/20%/20% split and keeping class proportions similar. This procedure was applied separately to each database in order to approximately maintain the proportions of signals from the three databases in the subsets for training, validation, and testing. The rationale for this approach was to avoid any subject overlap between the three subsets. The breakdown for each class and each subset is summarized in Table 2. In addition, as the proportion of signals labeled as *other rhythm* was very low (<2%), we repeated the procedure to split the data into training, validation, and test sets while excluding this label. The objective was then to differentiate between normal rhythm and atrial fibrillation only with a binary classifier. In this case, the breakdown is reported in Table 3. This dataset will be referred to as the PhysioNet dataset from now on.
Fig. 2. Examples of ECG records from the dataset of the challenge of Computing in Cardiology 2017: (A) normal rhythm from record A00026, (B) atrial fibrillation from record A00102, (C) normal rhythm from record A00007, (D) atrial fibrillation from record A00405.

Table 2. Breakdown of training, validation, and test sets for the dataset combining three databases from PhysioNet with three classes.

| Class               | Training | Validation | Test     |
|---------------------|----------|------------|----------|
| Normal rhythm       | 132474   | 43828      | 44080    | (44.7%)  |
| Atrial fibrillation | 158832   | 53972      | 52028    | (52.8%)  |
| Other rhythm        | 4816     | 1862       | 2420     | (2.5%)   |
| Total               | 296122   | 99662      | 98528    | (100%)   |
Table 3. Breakdown of training, validation, and test sets for the dataset combining three databases from PhysioNet with two classes.

| Class              | Training | Validation | Test  |
|--------------------|----------|------------|-------|
| Normal rhythm      | 133150   | 43132      | 44100 |
| Atrial fibrillation| 159180   | 53250      | 52402 |
| Total              | 292330   | 96382      | 96502 |

2.2 Pre-processing

After splitting both datasets into training, validation, and test sets, the signals were pre-processed before using them as inputs to the neural networks. The first step was to apply a digital Butterworth band-pass filter between 0.5 and 40 Hz. The filter was applied twice, once forward and once backward, to avoid phase distortion. The specifications were chosen based on the analog filter included in the device used to record the CinC 2017 dataset. Then, the signals were resampled to 200 Hz in order to standardize the sampling frequency across datasets. Finally, the signals were scaled by the mean of the standard deviations estimated over the training set. Scaling was shown to be helpful to accelerate training [18]. It is worth mentioning that the scaling operation was performed separately for each database in the PhysioNet dataset to take into account potential differences in ECG amplitude.

2.3 Network Architectures

Special care must be taken to handle signals with different lengths like the ones in the first dataset. A simple solution would be to truncate all signals to the length of the shortest one. This would make it possible to use a convolutional network to automatically extract high-level features for classification. However, it is not clear which part (beginning, middle, or end) of longer signals to keep. More importantly, it would waste a huge amount of data, especially for the first dataset where the shortest signal is around 9 seconds and the longest around 60 seconds.

A more appropriate approach is to use recurrent networks. Indeed, this class of neural networks are well-suited to take into account sequences with different lengths as they can, by design, remember past values for long periods of time. However, they are not as efficient for extracting high-level features compared to convolutional networks.

We recently proposed a neural network architecture combining convolutional and recurrent layers to classify cardiac arrhythmia [27]. It was selected as it uses the strong points of both types of layers: convolutional layers to extract high-level features and recurrent layers to handle signals with different lengths. In this paper, we extend this architecture and test different variations.
Each ECG signal is divided into sliding windows with 50% overlap. We selected two window sizes: 512 and 1024 samples corresponding approximately to 2.5 and 5 seconds as the signals are sampled at 200 Hz. The number of windows extracted from each signal depended on its duration. For 30-second signals, the most common duration, this resulted in 22 windows with 512 samples and 10 windows with 1024 samples. Convolutional layers were then applied to all windows of a signal. Each convolutional layer is composed of a one-dimensional convolution and a max pooling operation. The convolution used a kernel of size 5, zero padding, and a ReLU activation function. The max pooling operation used a pool size of 2. The first convolutional layer has 8 output channels and the subsequent layers double the number of output channels. Therefore, the number of channels is doubled at each layer while the window size is halved since the max pooling operation downsamples windows by two. We tested using 7 and 8 of these convolutional layers. Then, a global average pooling layer is applied to prepare features for the next step. The features are fed to a long short-term memory (LSTM) layer with 128 units. Finally, a softmax layer outputs the probability of each class for the input ECG windows. When training a neural network with the second dataset without the other rhythm class, the softmax layer is replaced by a logistic layer since there are only two classes. The three considered architectures are summarized in Table 4 with the approximate numbers of parameters. It is worth mentioning that we did not try to apply an eighth convolutional layer when using a window size of 512. The reason is that after the seventh layer, the window size is reduced to 4. Thus, it does not make sense to apply an additional convolutional layer with a kernel of size 5 to such short windows.

2.4 Data Augmentation

The CinC 2017 dataset is relatively small for fitting a neural network with only 6000 signals in the training set. Therefore, we applied two strategies to synthetically augment the number of ECG signals available. The first strategy is to simply flip the sign of each signal with probability 0.5. This strategy is particularly useful for the CinC 2017 dataset where, as mentioned previously, many signals are inverted since the recording device lacks a clear usage orientation. Indeed, we found it easier to let the neural networks learn to take into account inverted signals than developing an approach for detecting and rectifying such signals before training. There is no clear justification to apply this strategy to the PhysioNet dataset. Therefore, we trained the neural networks for this dataset with and without random sign flipping.

The second strategy for data augmentation uses the fact that, when extracting sliding windows, it is not possible to use all samples for the large majority of ECG signals. Indeed, the maximum number \( N \) of sliding windows of size \( W \) with 50% overlap in a signal with \( M \) samples is given by

\[
N = \left\lfloor \frac{2(M - W)}{W} \right\rfloor + 1
\]
Table 4. Neural network architectures. The output size of convolutional layers is given as $N \times W \times C$ where $N$ is the number of windows, $W$ is the window size, and $C$ is the number of channels. The number of classes is denoted by $K$ and the number of convolutional layers by $L$.

| Layer                      | $W = 512, L = 7$ | $W = 1024, L = 7$ | $W = 1024, L = 8$ |
|----------------------------|------------------|-------------------|------------------|
| Input windows              | $N \times 512 \times 1$ | $N \times 1024 \times 1$ | $N \times 1024 \times 1$ |
| Convolutional layer 1      | $N \times 256 \times 8$ | $N \times 512 \times 8$ | $N \times 512 \times 8$ |
| Convolutional layer 2      | $N \times 128 \times 16$ | $N \times 256 \times 16$ | $N \times 256 \times 16$ |
| Convolutional layer 3      | $N \times 64 \times 32$ | $N \times 128 \times 32$ | $N \times 128 \times 32$ |
| Convolutional layer 4      | $N \times 32 \times 64$ | $N \times 64 \times 64$ | $N \times 64 \times 64$ |
| Convolutional layer 5      | $N \times 16 \times 128$ | $N \times 32 \times 128$ | $N \times 32 \times 128$ |
| Convolutional layer 6      | $N \times 8 \times 256$ | $N \times 16 \times 256$ | $N \times 16 \times 256$ |
| Convolutional layer 7      | $N \times 4 \times 512$ | $N \times 8 \times 512$ | $N \times 8 \times 512$ |
| Convolutional layer 8      | $N \times 4 \times 1024$ |                       |                  |
| Global average pooling     | $N \times 512$ | $N \times 512$ | $N \times 1024$ |
| LSTM layer                 | 128              | 128                | 128              |
| Softmax (or logistic) layer| $K \ (1)$        | $K \ (1)$          | $K \ (1)$        |
| Number of parameters       | 1.2M             | 1.2M               | 4.1M             |
assuming \( M \geq W \). In the previous expression, \([\cdot]\) denotes the floor function. We took advantage of this observation to place the first window at a random offset from the start of the signal. This random offset is drawn uniformly from \( \{0, 1, 2, \ldots, M - (N - 1) \cdot \frac{W}{2} - W\} \) for each signal at each epoch. The rationale behind this strategy is to prevent the neural network from learning the precise positions of the QRS complexes in the signals from the training set. However, to avoid wasting ECG samples, we always used the maximum possible number of sliding windows for each signal. Finally, it is also important to mention that these data augmentation strategies were only applied during training and not during evaluation.

2.5 Training

We implemented our neural networks and the associated training pipeline with data augmentation in Python with the Keras package \([2]\). We trained the different neural network architectures for 100 epochs by minimizing the cross-entropy with the Adam algorithm \([16]\). We set the initial learning rate to 0.0005. The learning rate was divided by two if the cross-entropy evaluated on the validation set did not decrease for 5 consecutive epochs with a lower limit at \(10^{-5} \).

The batch size was set to 50 signals. We applied zero padding to ensure that all signals in a batch had the same number of samples. Specifically, signals that were too short were prepended with all-zero windows. To limit zero padding as much as possible, we sorted the signals by duration and grouped them in batches of similar lengths. This resulted in batches with varying number of windows.

The LSTM layer was regularized by applying dropout with a rate of 0.5 to both the input and recurrent parts \([25, 7]\). We monitored the accuracy on the validation set and selected the weights at the best epoch as the parameters for evaluation for each dataset and neural network architecture.

3 Results

We evaluated the three neural network architectures described in Table 4 on the CinC 2017 and PhysioNet datasets. The PhysioNet dataset was used with all three classes and after discarding the other rhythm class due its low proportion. Furthermore, we tried training neural networks on this dataset with and without the data augmentation strategy consisting in random flipping the sign of ECG signals. Indeed, flipping signal signs might be detrimental to classification accuracy since the PhysioNet dataset should not include inverted ECG records. After selecting the best neural networks for all cases, we evaluated them without zero padding by selecting a batch size of 1. The classification accuracy measured on the training, validation, and test sets are shown in Figure 3. In addition, the accuracy measured on the test set is reported in Table 5.

The best results on the CinC 2017 dataset were obtained with a neural network taking sliding windows with 1024 samples as input and extracting features
Fig. 3. Cardiac rhythm classification accuracy evaluated on training, validation, and test sets for each dataset and each architecture. The window size is denoted by $W$ and the number of convolutional layers by $L$. 
Table 5. Cardiac rhythm classification accuracy evaluated on the test set for each dataset and each architecture. The window size is denoted by $W$ and the number of convolutional layers by $L$. The best accuracy for each dataset is shown in bold.

| Dataset                  | $W = 512, L = 7$ | $W = 1024, L = 7$ | $W = 1024, L = 8$ |
|--------------------------|------------------|------------------|------------------|
| CinC 2017 dataset        | 0.8521           | 0.8623           | 0.8560           |
| PhysioNet dataset        |                  |                  |                  |
| 3 classes                | **0.9202**       | 0.9147           | 0.9121           |
| 3 classes, no random flip| 0.9056           | 0.9117           | 0.7967           |
| 2 classes                | 0.9234           | **0.9289**       | 0.9149           |
| 2 classes, no random flip| 0.9216           | 0.9211           | 0.9221           |

with 7 convolutional layers. The accuracy on the test set was 86.23%. Despite applying dropout, there was overfitting as shown by the difference in accuracy between the training, validation, and test sets. It also appears that using an additional convolutional layer did not help to improve generalization performance. By contrast, using a window size of 1024 instead of 512 was beneficial in terms of classification accuracy. However, the performance difference between the three considered architectures was limited to around 1% on the test set. We also computed the score used to evaluate the participants of the challenge of Computing in Cardiology 2017 (1) for our best network. It achieved a score of 0.829 on our test set which is comparable to the winning entries (0.83 [26,4,33,12]). However, it is important to note that we could not evaluate the score on the test set used during the challenge as it remains private at the time of writing this paper. Instead, we had to split the official training set into smaller sets for training, validation, and testing which reduced the available data.

We considered two cases on the PhysioNet dataset: training with three classes (normal rhythm, atrial fibrillation, and other rhythm) and training with two classes (by discarding the class for other rhythm). In the first case, the best architecture used a window size of 512 and 7 convolutional layers for feature extraction and achieved an accuracy of 92.02%. Using a larger window size or an additional convolutional layer did not help to increase classification accuracy. In the second case, a window size of 1024 and 7 convolutional layers led to the best performance on the test set with an accuracy of 92.89%. This is an expected improvement compared to the first case since we dropped the class with the least number of signals.

A few observations can be made after reviewing the results obtained on the PhysioNet dataset. First, it appears that randomly flipping the sign of ECG signals during training helped to improve classification accuracy. Indeed, the performance on the test was better for both two and three classes when this data augmentation strategy was used during training. This result is unexpected
as the PhysioNet dataset should not include inverted ECG signals. It is possible that this strategy, by introducing more diversity during training, led to slightly better generalization performance.

The second observation is that there is little difference in terms of classification accuracy between the three considered neural network architectures. Indeed, the maximum difference was less than 2% in all cases on the test set. In particular, a window size of 512 was better for the case with three classes while, in the binary case, a window size of 1024 yielded a better classification accuracy. However, it seems that using more than 7 convolutional layers to extract high-level features is not advantageous.

The third observation that comes to mind is the large gap in accuracy due to overfitting between training and validation sets on the one hand and test set on the other hand. Indeed, training set accuracy was usually above 98% and validation set accuracy decrease only slightly while test set accuracy was 6 or 7% lower. The small difference between the first two subsets can be explained by the fact that we monitored performance on the validation set to select the best weights for the neural networks. A possible explanation for the drop in performance observed on the test set is the approach used for splitting the original dataset. Indeed, we ensured that data for one subject was used either for training or for evaluation (but never for both). In other words, there is no overlap between subjects in the training, validation, and test sets. Thus, it is possible that the ECG signals recorded from subjects assigned to the test set are sufficiently different to cause this performance gap. It can also be partly explained by the presence of ECG signals with poor quality in the test set. An example of such signals is shown in Figure 4. Due to the poor signal quality, this signal was misclassified as atrial fibrillation instead of normal rhythm. We were also unable to reliably extract the RR intervals. Figure 5 shows another example of misclassification. However, the signal quality is good in the case. It seems the neural network predicted atrial fibrillation instead of normal rhythm due to relatively due the the variations in RR intervals. Indeed, atrial fibrillation is not associated with heart rates below 60 bpm.

Despite the observed overfitting, the classification accuracy measured on the test set was above 90% except for a single case (3 classes, no random sign flipping, window size of 1024, and 8 convolutional layers). We obtained these results on 30-second signals. A simple yet effective post-processing method to improve classification performance would be to apply a neural network on several consecutive 30-second segments and then pick the class with the most predictions as the output. Of course, such an approach is only applicable when ECG signals longer than 30 seconds are available.

4 Discussion

The classification performance of the neural network architectures we developed was similar to the winners of the challenge of Computing in Cardiology 2017. However, we could only evaluate their performance on a subset of the original
Fig. 4. Example of ECG signal with poor quality labeled as *normal rhythm* (top) and corresponding RR intervals (bottom) from the PhysioNet dataset. Due to poor signal quality, the RR intervals could not be extracted reliably.

Fig. 5. Example of ECG signal labeled as *normal rhythm* (top) and corresponding RR intervals (bottom) from the PhysioNet dataset.
training data since the official test set has not been publicly released yet. We also applied these network architectures to a dataset combining three databases from PhysioNet. The classification accuracy was above 92% when grouping together or discarding rhythms that were neither normal rhythm nor atrial fibrillation.

The three neural network architectures we considered combined convolutional and recurrent layers. The convolutional layers were used to extract high-level features from signal windows. Indeed, there is no need for feature engineering with this approach as these layers learn features relevant for arrhythmia classification during training directly from ECG data. Consequently, we applied only a band-pass filter and scaling during pre-processing to make training faster. The recurrent layer was used to take into account signals with different lengths as the CinC 2017 dataset includes ECG records ranging from 9 to 60 seconds. As all signals had a duration of 30 seconds in the PhysioNet dataset, it might have been more appropriate to avoid using recurrent layers. However, we were interested in estimating the performance of same architectures on a different dataset. Using only convolutional layers in this case might lead to better performance.

We also applied two strategies for data augmentation. The first one was to randomly flip the sign of each ECG signal during training. The main reason for using such a strategy was to let the neural networks learn to take into account inverted signals included in the CinC 2017 dataset. Surprisingly, this strategy also proved to be effective for the PhysioNet dataset which should not include inverted signals. Random sign flipping most likely helped to increase diversity during training. The second strategy for data augmentation was to apply random offsets from the start of each signal during training to prevent the neural networks from learning the exact locations of QRS complexes.

Collectively, these results demonstrate that detecting cardiac arrhythmia with neural networks from raw ECG signals is feasible. And even if classification accuracy is imperfect, they can help to select and extract segments with potential abnormal rhythms from long ECG recordings for further analysis by a trained specialist. If needed, a 12-lead ECG can then be performed to confirm or refine the diagnosis.

Despite these promising results, there is room for improvements. First, the CinC 2017 dataset is relatively small with only 8528 records. Comparatively, the PhysioNet dataset is much larger. However, it only includes records from 154 subjects and thus lacks diversity. In addition, several abnormal rhythms were either grouped together or simply discarded due to the limited number of available examples. The number of different subjects with these rhythms is even lower. Therefore, there is a need for datasets including ECG records from a large number of subjects with many examples of each rhythm. Obviously, this is a difficult task as building such a dataset would be costly and time-consuming. It is also important to note that we decided to use each lead of the PhysioNet dataset independently in order to use the same architectures for both datasets. Using both leads as two input channels might help to better identify abnormal heart rhythms. In addition, as the field of neural networks is rapidly evolving, several modifications are possible for the neural network architectures.
we considered in this paper. In particular, residual connections \cite{10, 31} as well as dense connections \cite{13} have shown impressive results in the context of image processing. These approaches might also be useful for processing time series in general and ECG signals in particular.

5 Conclusion

We applied three neural network architectures combining convolutional and recurrent layers to two datasets of ECG data for the detection and classification of cardiac arrhythmia. However, in the considered datasets, several rhythms with only a few available examples had to be grouped together. Future developments will need to tackle this issue by either using additional data from other databases or by learning to recognize arrhythmia with few examples. Furthermore, several modifications to our network architecture, such as skip connections, might help to improve generalization performance.

Acknowledgements

We would like to thank Clémentine Aguet and João Jorge for their helpful comments and suggestions.

References

1. Camm, A.J., et al.: Guidelines for the management of atrial fibrillation. European Heart Journal 31(19), 2369–2429 (2010)
2. Chollet, F., et al.: Keras. https://keras.io (2015)
3. Clifford, G.D., Liu, C., Moody, B., Lehman, L.W.H., Silva, I., Li, Q., Johnson, A.E., Mark, R.G.: AF classification from a short single lead ECG recording: The PhysioNet/Computing in Cardiology Challenge 2017. Proceedings of Computing in Cardiology 44, 1 (2017)
4. Datta, S., Puri, C., Mukherjee, A., Banerjee, R., Choudhury, A.D., Singh, R., Ukil, A., Bandyopadhyay, S., Pal, A., Khandelwal, S.: Identifying normal, AF and other abnormal ECG rhythms using a cascaded binary classifier. In: 2017 Computing in Cardiology (CinC). pp. 1–4 (2017)
5. De Chazal, P., O’Dwyer, M., Reilly, R.B.: Automatic classification of heartbeats using ECG morphology and heartbeat interval features. IEEE Transactions on Biomedical Engineering 51(7), 1196–1206 (2004)
6. Frick, M., Frykman, V., Jensen-Urstad, M., Östergren, J.: Factors predicting success rate and recurrence of atrial fibrillation after first electrical cardioversion in patients with persistent atrial fibrillation. Clinical Cardiology 24(3), 238–244 (2001)
7. Gal, Y., Ghahramani, Z.: A theoretically grounded application of dropout in recurrent neural networks. In: Advances in neural information processing systems. pp. 1019–1027 (2016)
8. Goldberger, A.L., Amaral, L.A.N., Glass, L., Hausdorff, J.M., Ivanov, P.C., Mark, R.G., Mietus, J.E., Moody, G.B., Peng, C.K., Stanley, H.E.: Physiobank, physiotoolkit, and physionet: Components of a new research resource for complex physiologic signals. Circulation 101(23), e215–e220 (2000)
9. Hahnloser, R.H.R., Sarpeshkar, R., Mahowald, M.A., Douglas, R.J., Seung, H.S.: Digital selection and analogue amplification coexist in a cortex-inspired silicon circuit. Nature 405(6789), 947 (2000)

10. He, K., Zhang, X., Ren, S., Sun, J.: Deep residual learning for image recognition. arXiv e-prints arXiv:1512.03385 (2015)

11. Hochreiter, S., Schmidhuber, J.: Long short-term memory. Neural Computation 9(8), 1735–1780 (1997)

12. Hong, S., Wu, M., Zhou, Y., Wang, Q., Shang, J., Li, H., Xie, J.: ENCASE: An ENSemble CIASsiEr for ECG classification using expert features and deep neural networks. In: 2017 Computing in Cardiology (CinC). pp. 1–4 (2017)

13. Huang, G., Liu, Z., van der Maaten, L., Weinberger, K.Q.: Densely connected convolutional networks. In: The IEEE Conference on Computer Vision and Pattern Recognition (CVPR) (2017)

14. January, C.T., Wann, L.S., Alpert, J.S., Calkins, H., Cigarroa, J.E., Cleveland, J.C., Conti, J.B., Ellinor, P.T., Ezekowitz, M.D., Field, M.E., Murray, K.T., Sacco, R.L., Stevenson, W.G., Tchou, P.J., Tracy, C.M., Yancy, C.W.: 2014 AHA/ACC/HRS guideline for the management of patients with atrial fibrillation: a report of the American College of Cardiology/American Heart Association task force on practice guidelines and the Heart Rhythm Society. Journal of the American College of Cardiology 64(21), e1–e76 (2014)

15. Kannel, W.B., Wolf, P.A., Benjamin, E.J., Levy, D.: Prevalence, incidence, prognosis, and predisposing conditions for atrial fibrillation: population-based estimates. The American journal of cardiology 82(7), 2N–9N (1998)

16. Kingma, D.P., Ba, J.: Adam: A method for stochastic optimization. arXiv e-prints arXiv:1412.6980 (2014)

17. Krizhevsky, A., Sutskever, I., Hinton, G.E.: ImageNet classification with deep convolutional neural networks. In: Advances in Neural Information Processing Systems 25. pp. 1097–1105 (2012)

18. LeCun, Y.A., Bottou, L., Orr, G.B., Müller, K.R.: Efficient backprop. In: Neural networks: Tricks of the trade, pp. 9–48. Springer (2012)

19. Moody, G.B., Mark, R.G.: A new method for detecting atrial fibrillation using RR intervals. In: Computers in Cardiology. pp. 227–230 (1983)

20. Moody, G.B., Mark, R.G.: The impact of the MIT-BIH arrhythmia database. IEEE Engineering in Medicine and Biology Magazine 20(3), 45–50 (2001)

21. Nattel, S., Burstein, B., Dobrev, D.: Atrial remodeling and atrial fibrillation: mechanisms and implications. Circulation: Arrhythmia and Electrophysiology 1(1), 62–73 (2008)

22. Owis, M.I., Abou-Zied, A.H., Youssef, A.B.M., Kadah, Y.M.: Study of features based on nonlinear dynamical modeling in ECG arrhythmia detection and classification. IEEE Transactions on Biomedical Engineering 49(7), 733–736 (2002)

23. Petrutiu, S., Sahakian, A.V., Swiryn, S.: Abrupt changes in fibrillatory wave characteristics at the termination of paroxysmal atrial fibrillation in humans. Europace 9(7), 466–470 (2007)

24. Rajpurkar, P., Hannun, A.Y., Haghpahan, M., Bourn, C., Ng, A.Y.: Cardiologist-level arrhythmia detection with convolutional neural networks. arXiv e-prints arXiv:1707.01836 (2017)

25. Srivastava, N., Hinton, G., Krizhevsky, A., Sutskever, I., Salakhutdinov, R.: Dropout: a simple way to prevent neural networks from overfitting. The Journal of Machine Learning Research 15(1), 1929–1958 (2014)
26. Teijeiro, T., García, C.A., Castro, D., Félix, P.: Arrhythmia classification from the abductive interpretation of short single-lead ECG records. In: 2017 Computing in Cardiology (CinC). pp. 1–4 (2017)

27. Van Zaen, J., Chételat, O., Lemay, M., Calvo, E.M., Delgado-Gonzalo, R.: Classification of cardiac arrhythmias from single lead ecg with a convolutional recurrent neural network. arXiv e-prints arXiv:1907.01513 (2019)

28. Wang, T.J., Larson, M.G., Levy, D., Vasan, R.S., Leip, E.P., Wolf, P.A., D’Agostino, R.B., Murabito, J.M., Kannel, W.B., Benjamin, E.J.: Temporal relations of atrial fibrillation and congestive heart failure and their joint influence on mortality: the Framingham heart study. Circulation 107(23), 2920–2925 (2003)

29. Wijffels, M.C.E.F., Kirchhof, C.J.H.J., Dorland, R., Allessie, M.A.: Atrial fibrillation begets atrial fibrillation. Circulation 92(7), 1954–1968 (1995)

30. Xia, Y., Wulan, N., Wang, K., Zhang, H.: Detecting atrial fibrillation by deep convolutional neural networks. Computers in Biology and Medicine 93, 84–92 (2018)

31. Xie, S., Girshick, R., Dollár, P., Tu, Z., He, K.: Aggregated residual transformations for deep neural networks. arXiv e-prints arXiv:1611.05431 (2016)

32. Xiong, Z., Stiles, M.K., Zhao, J.: Robust ECG signal classification for detection of atrial fibrillation using a novel neural network. In: 2017 Computing in Cardiology (CinC). pp. 1–4 (2017)

33. Zabihi, M., Rad, A.B., Katsaggelos, A.K., Kiranyaz, S., Narkilahti, S., Gabbouj, M.: Detection of atrial fibrillation in ECG hand-held devices using a random forest classifier. In: 2017 Computing in Cardiology (CinC). pp. 1–4 (2017)

34. Zhou, Y.T., Chellappa, R.: Computation of optical flow using a neural network. In: IEEE International Conference on Neural Networks. pp. 71–78 (1988)

35. Zihlmann, M., Perekrestenko, D., Tschannen, M.: Convolutional recurrent neural networks for electrocardiogram classification. In: 2017 Computing in Cardiology (CinC). pp. 1–4 (2017)