ECG Heartbeat Classification: A Deep Transferable Representation

Mohammad Kachuee, Shayan Fazeli, Majid Sarrafzadeh
University of California, Los Angeles (UCLA)

***Abstract*—Electrocardiogram (ECG) can be reliably used as a measure to monitor the functionality of the cardiovascular system. Recently, there has been a great attention towards accurate categorization of heartbeats. While there are many commonalities between different ECG conditions, the focus of most studies has been classifying a set of conditions on a dataset annotated for that task rather than learning and employing a transferable knowledge between different tasks. In this paper, we propose a method based on deep convolutional neural networks for the classification of heartbeats which is able to accurately classify five different arrhythmias in accordance with the AAMI EC57 standard. Furthermore, we suggest a method for transferring the knowledge acquired on this task to the myocardial infarction (MI) classification task. We evaluated the proposed method on PhysioNet's MIT-BIH and PTB Diagnostics datasets. According to the results, the suggested method is able to make predictions with the average accuracies of 93.4% and 95.9% on arrhythmia classification and MI classification, respectively.**

I. Introduction

To address the problems raised with the manual analysis of ECG signals, many studies in the literature explored using machine learning techniques to accurately detect the anomalies in the signal [1], [2]. Most of these approaches involve a preprocessing phase for preparing the signal. Afterwards, the handcrafted features which are mostly statistical summarizations of signal windows are extracted from these signals and used in further analysis for the final classification task. As for the inference engine, conventional machine learning approaches for ECG analysis include Support Vector Machines, multi-layer perceptrons, decision trees, etc.

These handcrafted features provide us with an acceptable representation of the signal, based on recent machine learning studies, automated feature extraction and representation methods are proven to be more scalable and are capable of making more accurate predictions. An end-to-end deep learning framework allows the machine to learn the features that are best suited to the specific task that it is dedicated to carry out. Deep learning approaches, however, contain a tremendously large amount of variables which require massive amounts of data to be trained. One way of dealing with the need to a massive amount of data is the concept of knowledge transfer between different tasks.

A Complete version of this paper is available at [3].

II. Datasets

In this paper, we use PhysioNet MIT-BIH Arrhythmia and PTB Diagnostic ECG Databases as data source for labeled ECG records [4]. Furthermore, we demonstrate that the knowledge learned from the former database can be successfully transferred for training inference models for the latter. In all of our experiments, we have used ECG lead II re-sampled to the sampling frequency of $125Hz$ as the input.

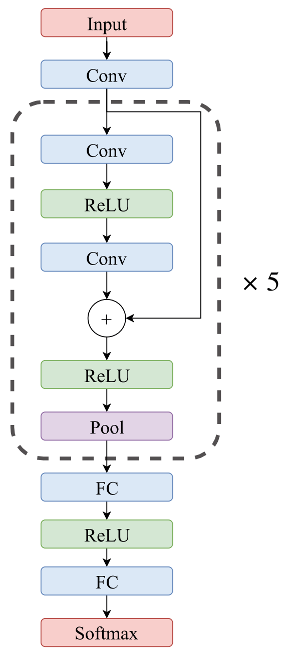


Fig. 1: Architecture of the proposed network.

III. Methodology

A. Preprocessing

As ECG beats are inputs of the proposed method we suggest cropping individual beats and zero padding them to a certain length.

B. Training the Arrhythmia Classifier

Here, we train a convolutional neural network for classification of ECG beat types on the MIT-BIH dataset. The trained network not only can be used for the purpose of beat classification, but also, in the next section, we show that it can be used as an informative representation of heartbeats.

Fig. 1 illustrates the network architecture proposed for the beat classification task. Extracted beats, as explained in Section III-A, are used as inputs. Here, all convolution layers

2575-2634/18/$31.00 ©2018 IEEE
DOI 10.1109/ICHI.2018.00092

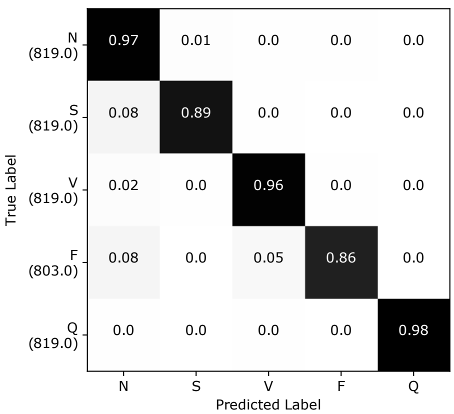
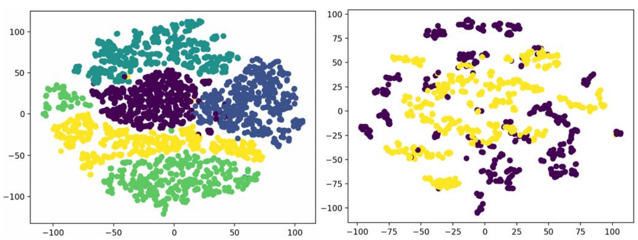


Fig. 2: Confusion matrix for heartbeat classification on the test set. Total number of samples in each class is indicated inside parenthesis.



(a) (b)

Fig. 3: t-SNE visualization of the learned representation: (a) samples from MIT-BIH for ECG beat classification (b) samples from PTB dataset for MI classification. Labels for each task are indicated with colors (best viewed in color).

are applying 1-D convolution through time and each have 32 kernels of size 5. We also use max pooling of size 5 and stride 2 in all pooling layers. The predictor network consists of five residual blocks followed by two fully-connected layers with 32 neurons each and a softmax layer to predict output class probabilities. Each residual block contains two convolutional layers, two ReLU nonlinearities, a residual skip connection, and a pooling layer. In total, the resulting network is a deep network consisting of 13 weight layers.

C. Training the MI Predictor

After training the network suggested in Section III-B, we use the output activations of the very last convolution layer as a representation of input beats. Here, we use this representation as input to a two layer fully-connected network with 32 neurons at each layer to predict MI. It is noteworthy to mention that during the training for the MI prediction task, we freeze the weights for all other layers aside from the last two. In other words, we only train the last two network layers and use the learned representation of Section III-B.

IV. RESULTS

TABLE I: Comparison of heartbeat classification results.

Work	Approach	Average Accuracy (%)
This Paper	**Deep residual CNN**	**93.4**
Acharya *et al.* [5]	Augmentation + CNN	93.5
Martis *et al.* [6]	DWT + SVM	93.8
Li *et al.* [7]	DWT + random forest	94.6

TABLE II: Comparison of MI classification results.

Work	Accuracy (%)	Precision (%)	Recall (%)
This Paper[1]	**95.9**	**95.2**	**95.1**
Acharya *et al.* [8][1]	93.5	92.8	93.7
Kojuri *et al.* [9][2]	95.6	97.9	93.3
Sun *et al.* [10][3]	–	82.4	92.6
Sharma *et al.* [11][3]	96	99	93

[1]: PTB dataset, ECG lead II
[2]: dataset collected by authors, 12-lead ECG
[3]: PTB dataset, 12-lead ECG

REFERENCES

[1] A. Esmaili, M. Kachuee, and M. Shabany, "Nonlinear cuffless blood pressure estimation of healthy subjects using pulse transit time and arrival time," *IEEE Transactions on Instrumentation and Measurement*, vol. 66, no. 12, pp. 3299–3308, 2017.

[2] A. E. Dastjerdi, M. Kachuee, and M. Shabany, "Non-invasive blood pressure estimation using phonocardiogram," in *Circuits and Systems (ISCAS), 2017 IEEE International Symposium on*. IEEE, 2017, pp. 1–4.

[3] M. Kachuee, S. Fazeli, and M. Sarrafzadeh, "Ecg heartbeat classification: A deep transferable representation," *arXiv preprint arXiv:1805.00794*, 2018.

[4] A. L. Goldberger, L. A. Amaral, L. Glass, J. M. Hausdorff, P. C. Ivanov, R. G. Mark, J. E. Mietus, G. B. Moody, C.-K. Peng, and H. E. Stanley, "Physiobank, physiotoolkit, and physionet," *Circulation*, vol. 101, no. 23, pp. e215–e220, 2000.

[5] U. R. Acharya, S. L. Oh, Y. Hagiwara, J. H. Tan, M. Adam, A. Gertych, and R. San Tan, "A deep convolutional neural network model to classify heartbeats," *Computers in biology and medicine*, vol. 89, pp. 389–396, 2017.

[6] R. J. Martis, U. R. Acharya, C. M. Lim, K. Mandana, A. K. Ray, and C. Chakraborty, "Application of higher order cumulant features for cardiac health diagnosis using ecg signals," *International journal of neural systems*, vol. 23, no. 04, p. 1350014, 2013.

[7] T. Li and M. Zhou, "Ecg classification using wavelet packet entropy and random forests," *Entropy*, vol. 18, no. 8, p. 285, 2016.

[8] U. R. Acharya, H. Fujita, S. L. Oh, Y. Hagiwara, J. H. Tan, and M. Adam, "Application of deep convolutional neural network for automated detection of myocardial infarction using ecg signals," *Information Sciences*, vol. 415, pp. 190–198, 2017.

[9] J. Kojuri, R. Boostani, P. Dehghani, F. Nowroozipour, and N. Saki, "Prediction of acute myocardial infarction with artificial neural networks in patients with nondiagnostic electrocardiogram," *Journal of Cardiovascular Disease Research Vol*, vol. 6, no. 2, p. 51, 2015.

[10] L. Sun, Y. Lu, K. Yang, and S. Li, "Ecg analysis using multiple instance learning for myocardial infarction detection," *IEEE transactions on biomedical engineering*, vol. 59, no. 12, pp. 3348–3356, 2012.

[11] L. Sharma, R. Tripathy, and S. Dandapat, "Multiscale energy and eigenspace approach to detection and localization of myocardial infarction," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 7, pp. 1827–1837, 2015.