Automatic Diagnosis of Short-Duration 12-Lead ECG using a Deep Convolutional Network

Antônio H. Ribeiro[1, 2], Manoel Horta Ribeiro[1], Gabriela Paixão[1, 3], Derick Oliveira[1], Paulo R. Gomes[1, 3], Jéssica A. Canazart[1], Milton Pifano[1, 3], Carl R. Andersson[2], Peter W. Macfarlane[4], Wagner Meira Jr[1]., Thomas B. Schön[2], Antonio Luiz Ribeiro[1, 3]

[1] Universidade Federal de Minas Gerais (Brazil), [2] Uppsala University (Sweden),
[3] Telehealth Center from Hospital das Clínicas de Minas Gerais (Brazil), [4] University of Glasgow(Scotland)

Introduction

End-to-end deep learning has achieved striking success on several tasks and there are great expectations about how this technology may improve health care and clinical practice. So far, however, no paper has used these techniques to automatically classify abnormalities for, *in-clinics, 12-lead electrocardiogram (ECG) exams.* This paper intend to fill this gap and improve the analysis of such exams that has the potential to provide a full evaluation of the heart activity. In remote areas without access to a cardiologist with full expertise in ECG diagnosis this automation can be very important.

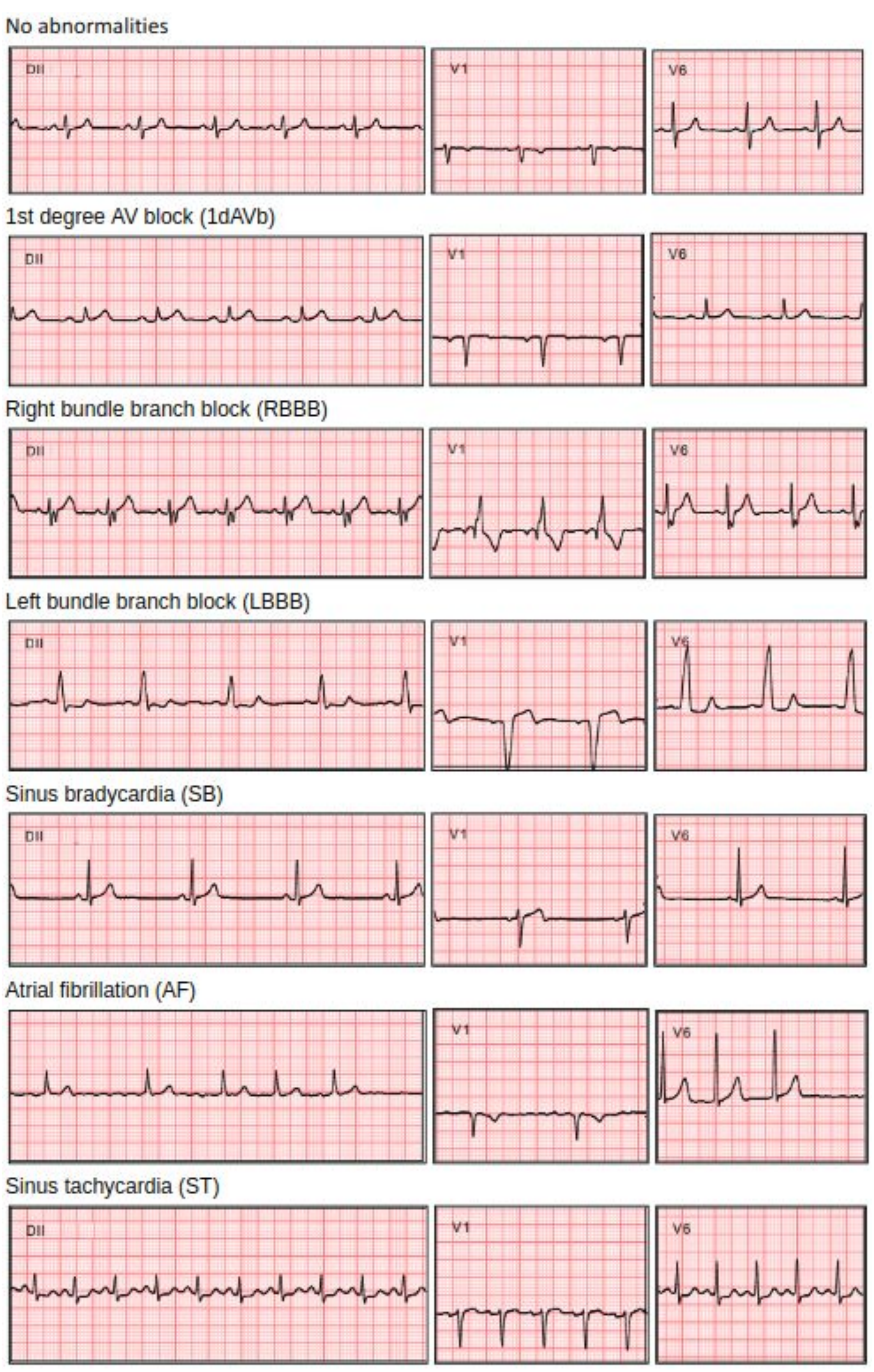
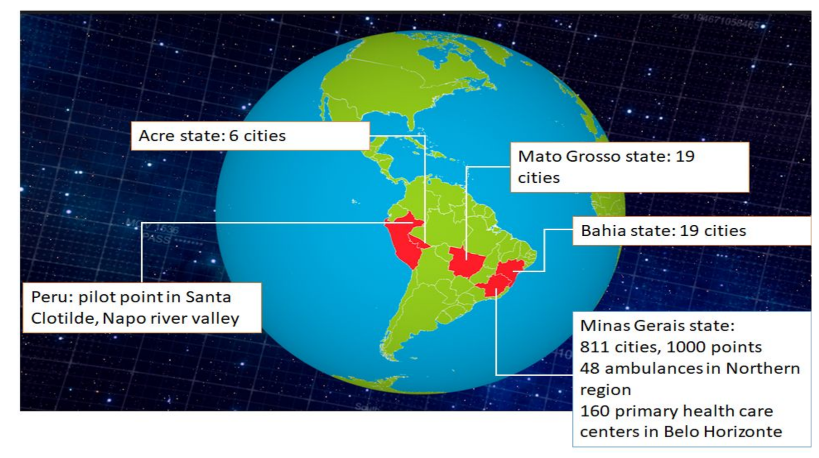


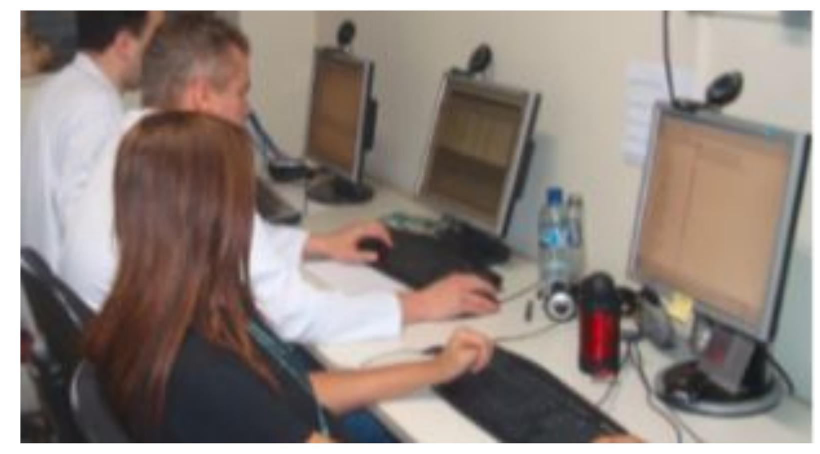
Figure: The abnormalities detected by the model.

Data

Training and validation - The dataset used for training and validating the model consists of *2,322,513 records from 1,676,384 different patients from 811 counties in the state of Minas Gerais/Brazil.* The duration of the ECG recordings is between 7 and 10 seconds. We split this dataset into a training (98%) and a validation (2%) set.

Testing - The dataset used for testing the model consists of *827 tracings from distinct patients annotated by three medical doctors with experience in electrocardiography.*





Model

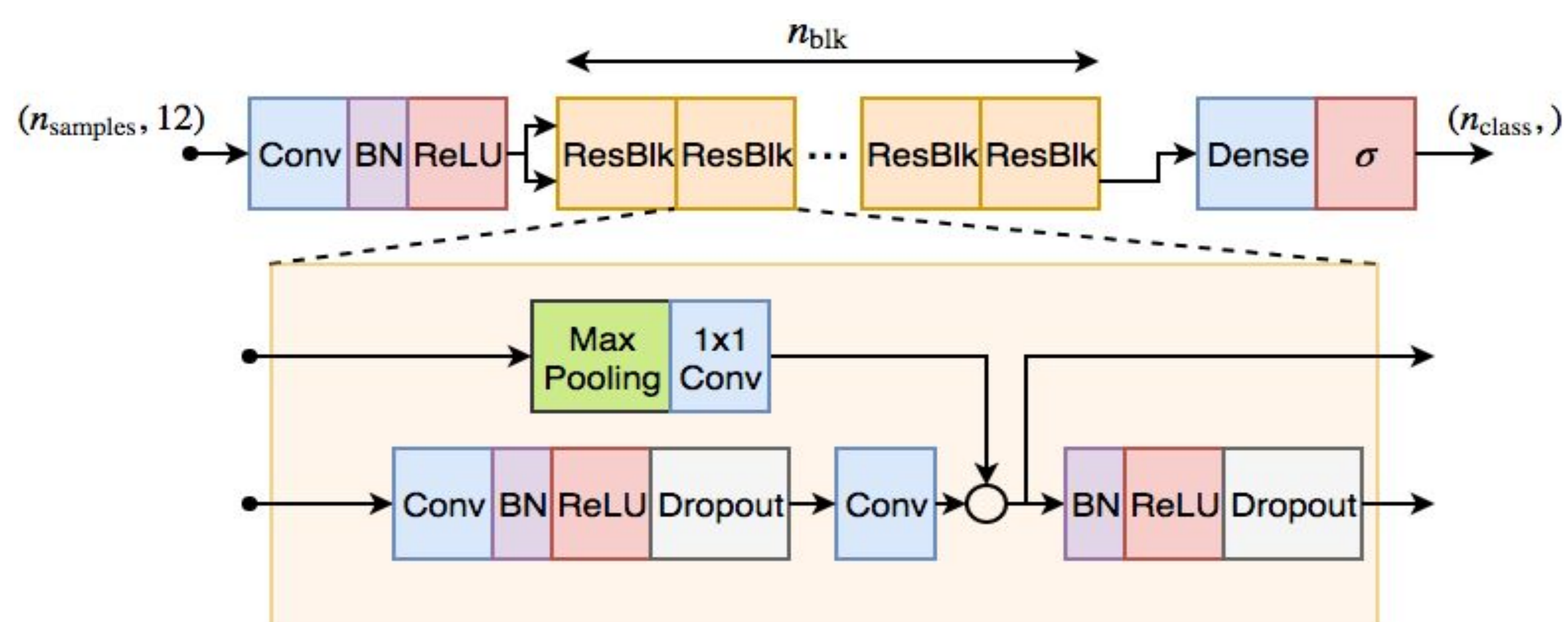


Figure: The unidimensional residual neural network (He et al., 2015) with 9 convolutional layers used for ECG classification (n_{blk} = 4). The architecture is similar to that of Rajpurkar et al. (2017).

Future work

- Extend to a large range of abnormalities. Other conditions are available in such a large dataset.
- We assess more than 2,000 digital ECGs per day. So there is a constant inflow of data that could be used in training, validating and testing future models.
- Implement and evaluate the model as part of a broader telehealth solution.

References

Antônio H. Ribeiro, Manoel Horta Ribeiro, Gabriela M. M. Paixão, Derick M. Oliveira, Paulo R. Gomes, Jéssica A. Canazart, Milton P. S. Ferreira, Carl R. Andersson, Peter W. Macfarlane, Wagner Meira Jr., Thomas B. Schön, and Antonio Luiz P. Ribeiro. Automatic Diagnosis of the Short-Duration 12-Lead ECG using a Deep Neural Network: the CODE Study. arXiv e-prints, page arXiv:1904.01949, Apr 2019.

He, Kaiming, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. *Deep residual learning for image recognition.* In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pp. 770-778. 2016.

A.Y. Hannun, P. Rajpurkar, H. Masoumeh, G.H. Tison, C. Bourn, M.P. Turakhia, A.Y. Ng.. *Cardiologist-level arrhythmia detection and classification in ambulatory electrocardiograms using a deep neural network.* Nature Medicine, 25(1), pp. 65-69. 2019.

Results

	Precision (PPV)				Recall (Sensitivity)				Specificity				F1 Score			
	DNN	cardio.	emerg.	stud.	DNN	cardio.	emerg.	stud.	DNN	cardio.	emerg.	stud.	DNN	cardio.	emerg.	stud.
1dAVb	0.893	0.905	0.639	0.605	0.893	0.679	0.821	0.929	0.996	0.997	0.984	0.979	**0.893**	0.776	0.719	0.732
RBBB	0.872	0.868	0.963	0.914	1.000	0.971	0.765	0.941	0.994	0.994	0.999	0.996	**0.932**	0.917	0.852	0.928
LBBB	0.968	1.000	0.963	0.931	1.000	0.900	0.867	0.900	0.999	1.000	0.999	0.997	**0.984**	0.947	0.912	0.915
SB	0.833	0.833	0.824	0.750	0.938	0.938	0.875	0.750	0.996	0.996	0.996	0.995	**0.882**	**0.882**	0.848	0.750
AF	0.800	0.769	0.800	0.571	0.923	0.769	0.615	0.923	0.996	0.996	0.998	0.989	**0.857**	0.769	0.696	0.706
ST	0.897	0.968	0.919	0.882	0.972	0.833	0.944	0.833	0.995	0.999	0.996	0.995	**0.933**	0.896	0.932	0.857

Table: Performance on the test set. Scores of our neural network compared with the average performance of: i) 4th year cardiology resident (*cardio.*); ii) 3rd year emergency resident (*emerg.*); and, iii) 5th year medical students (*stud.*)