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

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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.

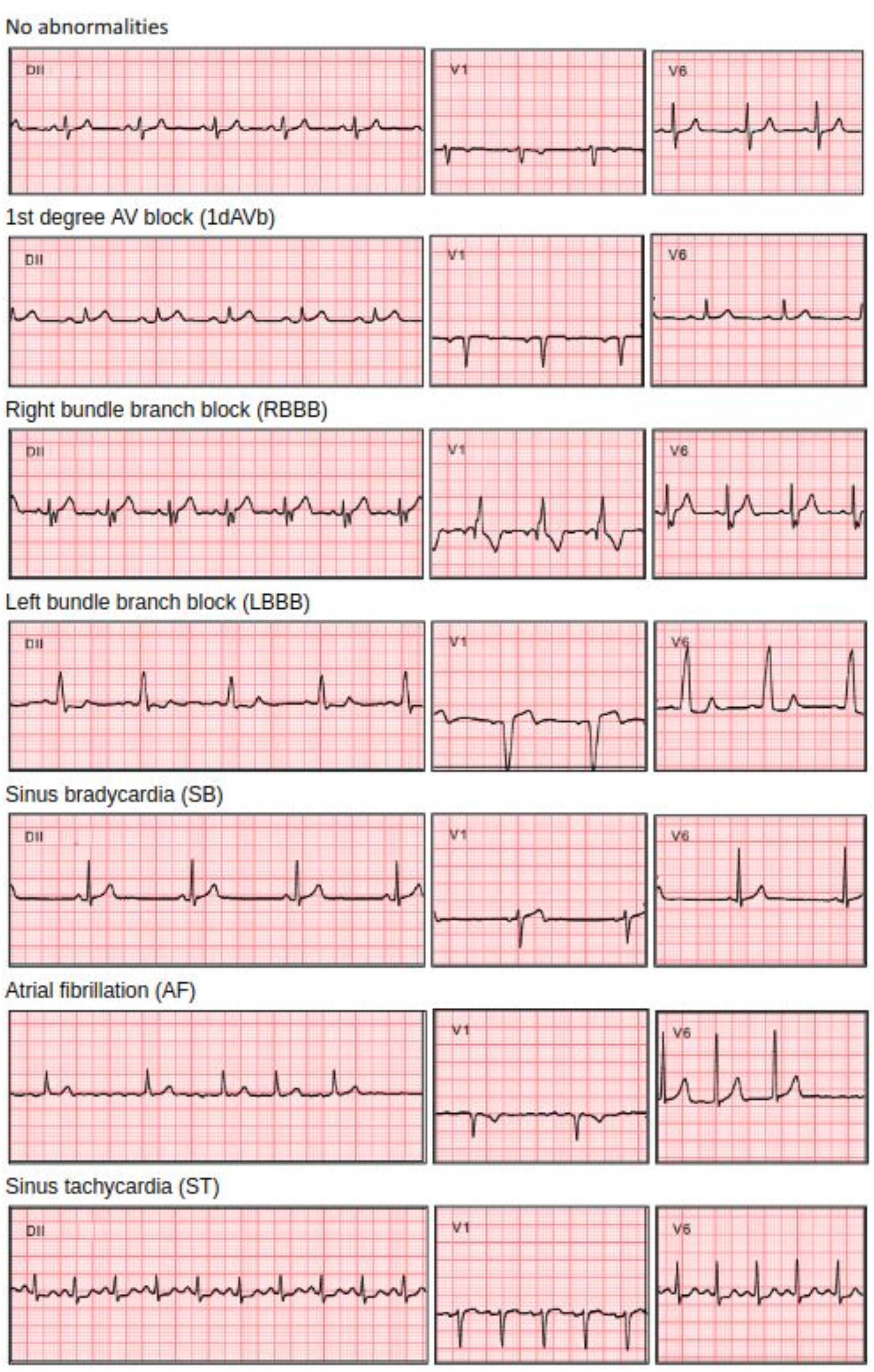


Figure: The abnormalities detected by the model.

Data

Training and validation - The dataset used for training and validating the model consists of *2,470,424 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 *953 tracings from distinct patients annotated by three medical doctors with experience in electrocardiography.*

Model

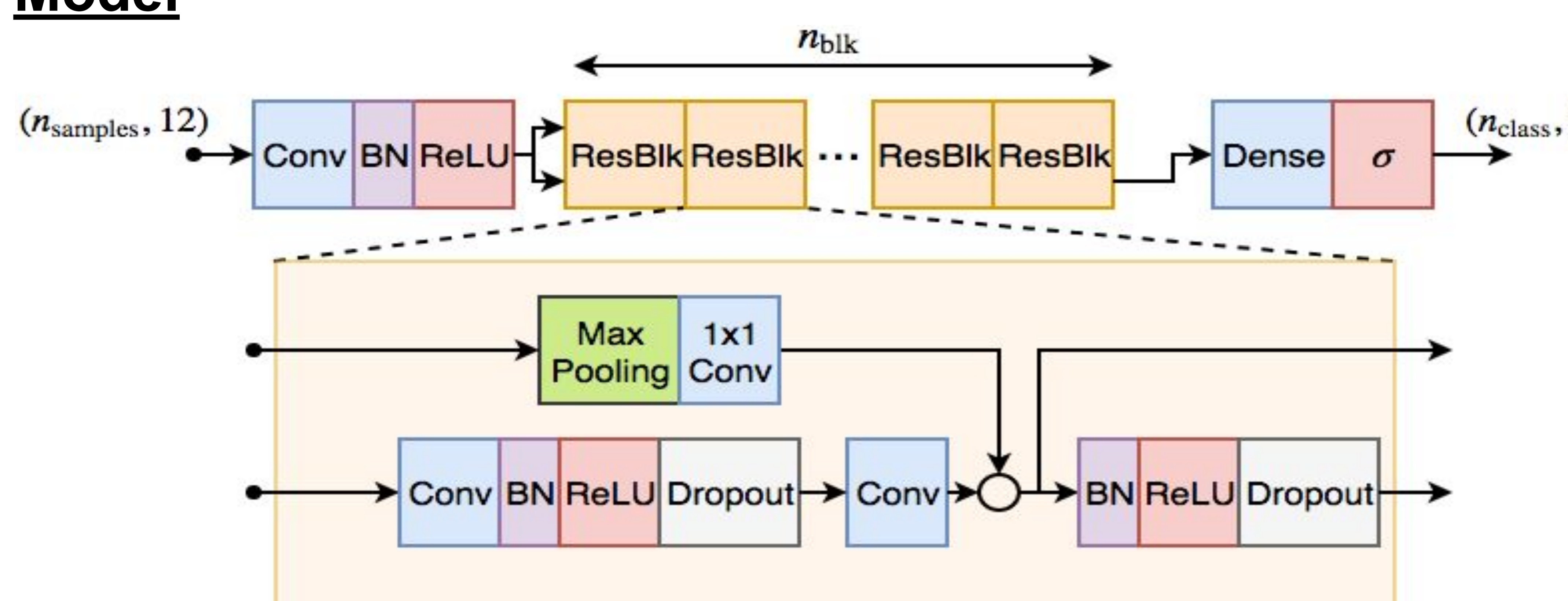


Figure: The unidimensional residual neural network (He et al., 2015) with 9 convolutional layers used for ECG classification (n_{blk} = 4). The architecture is similar to that of Rajpurkar et al. (2017).

Results

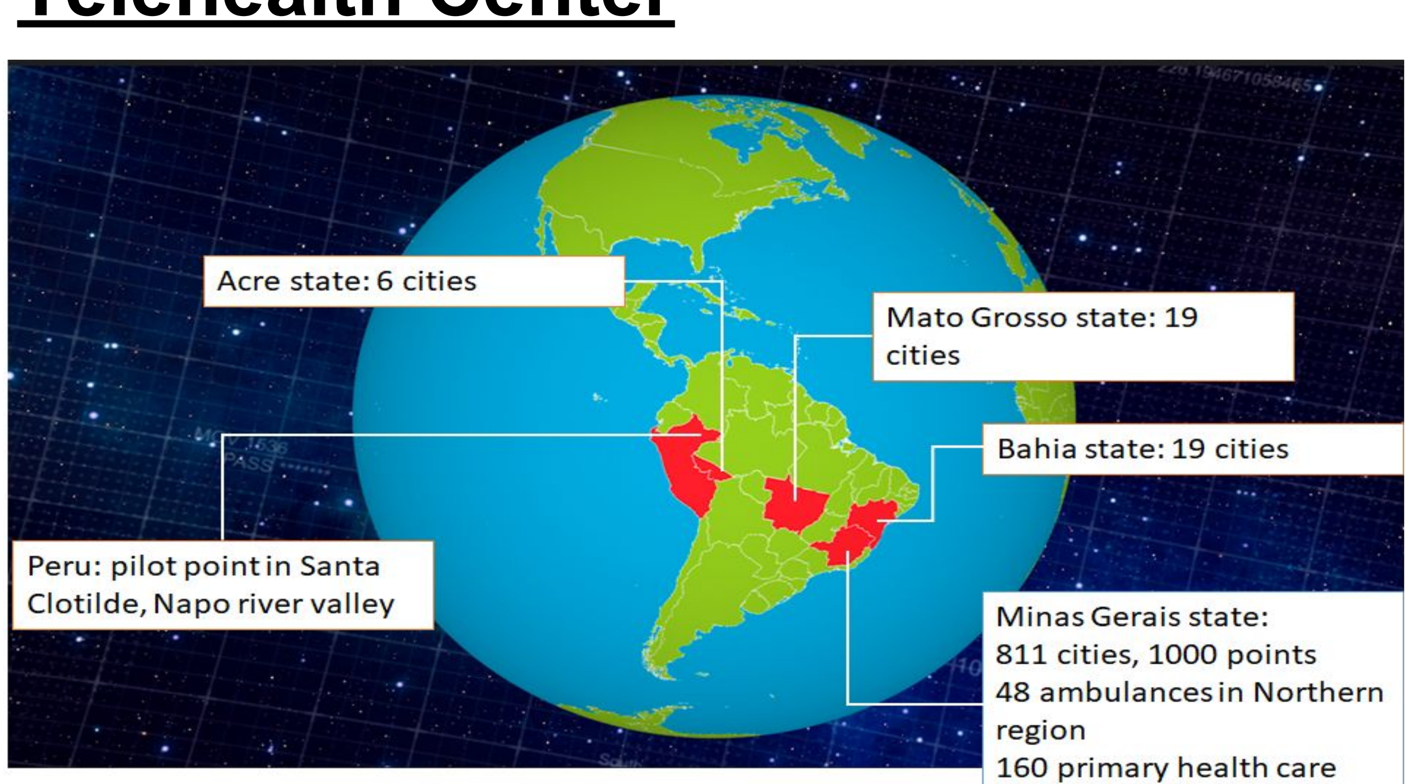
	Precision (PPV)		Recall (Sensitivity)		Specificity		F1 Score	
	model	doctor	model	doctor	model	doctor	model	doctor
1dAVb	0.923	0.905	0.727	0.679	0.998	0.998	**0.813**	0.776
RBBB	0.878	0.875	1.000	0.412	0.995	0.998	**0.935**	0.560
LBBB	0.971	1.000	1.000	0.900	0.999	1.000	**0.985**	0.947
SB	0.792	0.833	0.864	0.938	0.995	0.996	0.826	**0.882**
AF	0.846	0.769	0.846	0.769	0.998	0.996	**0.846**	0.769
ST	0.870	0.938	0.952	0.833	0.993	0.998	**0.909**	0.882

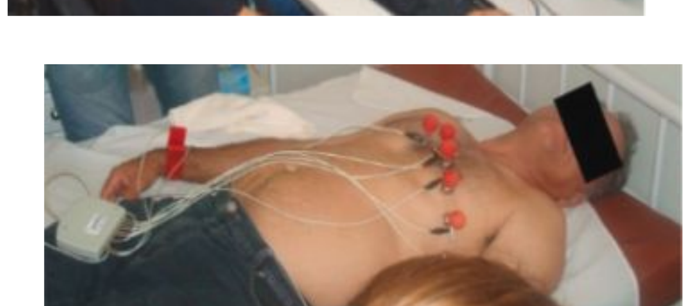
Table: Performance of our deep neural network model and 4th year cardiology resident medical doctors when evaluated on the test set

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.

Telehealth Center





References

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Pranav Rajpurkar, Awni Y. Hannun, Masoumeh Haghpanahi, Codie Bourn, and Andrew Y. Ng. *Cardiologist-Level Arrhythmia Detection with Convolutional Neural Networks.* arXiv:1707.01836, July 2017.

Acknowledgements