Teaching a Machine to Diagnose a Heart Disease
Beginning from digitizing scanned ECGs to detecting the Brugada Syndrome (BrS) *

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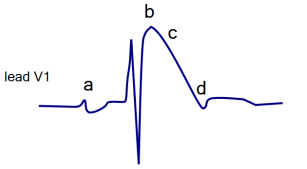
The Brugada Syndrome (BrS) is a severe cardiovascular disease that can lead to a sudden cardiac death even in patients with structurally normal hearts [2]. Ever since its first description [2], only one clear diagnostic case is acknowledged, characterized by an anomaly in the electrocardiogram (ECG); an accentuation of the J wave found in the right precordial leads (V1, V2), which results in an ST-segment elevation that is often followed by a negative T-wave [2], see Figure 1.



ECG characteristics in Brugada Syndrome
a. Broad P wave with some PQ prolongation
b. J point elevation
c. Coved type ST segment elevation
d. Inverted T wave

Fig. 1. The BrS positive pattern [7].

In the following, we present an automated pipeline that transformed scanned images of ECGs to time-voltage data, which is then used as basis for our long short-term memory (LSTM) [5, 3] classifier able to differentiate BrS positive ECGs from negative ones.

The digitization process follows an automatic pipeline that transforms scans of ECG images, comprising three distinctive image types (e.g., background and foreground color). A full description of the process can be found in [6].
First, the images are gray-scaled and rotated if needed. Then, obstacles, such as a black frame surrounding the signals or the background grid, are removed. Thirdly, we split the sequences into distinctive images by summing over the pixels in its columns. We use the minima in between peaks of pixels, each representing a single signal, as cut off points. Finally, every signal is upsampled and then mapped to time-voltage coordinates. For most of the ECG leads, the pipeline preserves the signals, see Figure 2. Yet, some sequences cannot be separated, leading to distortion.

The classifier's task is to read-in ECG images and make a binary decision of whether it is BrS positive or negative. We gathered positive ECGs (30 in total) with our pipeline while extracting negative examples (80 in total) from the PTB Database of Physionet [1], [4]. Our model is composed of a single LSTM-layer followed by a dropout layer and a sigmoid activation function for classification, its entire architecture and training process is described in the thesis [6].

* This work was supported by the project IRP8: IMAGica: an Integrative personalized Medical Approach for Genetic diseases, Inherited Cardiac Arrhythmias as a model.

Given the limited amount of data, the classifier scores a high amount of false positives, while avoiding any false negatives, see Table 1. In a medical context this might be favorable, as one would prefer to perform additional test rather than to miss a diagnosis, however, before it becomes relevant for any practical purpose, further improvements and testing has to be conducted.

		True		
		BrS+	BrS−	Total
Predicted	BrS+	22	45	67
	BrS−	0	24	24
	Total	22	69	91

Table 1. Confusion Matrix of our LSTM model.

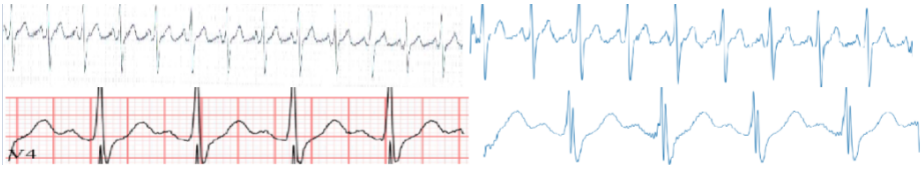


Fig. 2. The outcome of the digitization process for two ECG image types. The top image displays a good result the bottom image a distorted one.

We presented an automated pipeline capable of transforming scanned ECGs to time-voltage data. Furthermore, we explore the capabilities of the LSTM-based classifier on differentiating BrS positive ECGs from negative ones. Further research and experimentation are needed for obtaining a classifier achieving better performance. Another aspect is to investigate the role of different segments of the ECGs in the classification as positive for BrS.

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