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ECG RHYTHM RECOGNITION BY CONVOLUTIONAL NEURAL NETWORK

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According to the World Health Organization, cardiovascular disease (CVD) is the leading cause of death worldwide. The organization estimates that 17.9 million people died from CVD in 2016, accounting for 31% of all deaths in the world, 85% of these deaths were due to heart attack and stroke.

The main and most accessible way to diagnose CVD is ECG. The ability to receive, automatically recognize and make decisions based on ECG data obtained remotely provides doctors and patients with new ways to reduce these sad statistics.

Automatic recognition of ECG rhythms is already a classic task. Despite the fact that the first studies in the field of digital processing of ECG records appeared in the 70s of the last century, this area does not lose its relevance for health care and continues to develop. Mainly, the changes relate to the availability of continuous remote cardiac monitoring within telemedicine systems for ordinary patients.

In recent years, research on this topic has been focused on finding more accurate and less demanding algorithms for the initial data. Accuracy-enhancing automatic recognition techniques require an increasing amount of tagged data for training and testing models. The most accessible open data is collected on the PhysioBank project site. In addition, this resource is notable for the fact that it hosts annual competitions to highlight the properties of physiological data. In the 2017 competition, for example, the challenge was to isolate atrial fibrillation. The close recognition quality was given by two radically different approaches - feeding a large number of traditional indicators into the automatic algorithm and feeding the primary raw data to the neural network.

The classical approach to training recognition models provides for preliminary filtering of input data from mains pickups and broadband interference caused by electrode mobility and natural body currents of muscle origin. Often, QRS complexes are detected in the signal, and the data is sliced according to their position.

The option of directly feeding data to a trained neural network is certainly simpler from the point of view of data preparation and requires significantly less computational resources. Such networks can be based on the DCNN structure. According to the experience of recognizing AFIB (atrial fibrillation), recordings of 10 seconds are the right compromise between recognition accuracy and the desire to reduce the amount of simultaneously processed data.

First of all, patients 102 and 104 were excluded from the ECG records of 48 patients, who did not have the MLII lead, which was supposed to be examined. The research uses 15 rhythms that are already present in the layout. Due to the different number of records for different classes, the data of such classes are multiplied in order to equalize the cardinality of the classes. Data preprocessing consists only in subtracting the average. Normalization of the signal amplitude is not carried out, since it is known that a drop in amplitude is the most important sign of a critical state of a patient, for example, asystole. There is no asystole in the current data, but it is assumed that work will continue with the expansion of the data with records from other databases.

Data propagation for training "poor" classes is performed by sampling from a long implementation with overlapping 10-second windows. When examining the data, it can be seen that manual marking of rhythms contains a systematic error in the first segment due to the expert's preferred beginning of the rhythm relative to the strike phase, while a 10-second segment with real recognition can start from an arbitrary place. The windows are overlapped in increments of 1 second, so the intervals of the continuous rhythm are rounded down to the nearest second. This interval is centered relative to the origin, which gives a random start offset from zero to half a second (on average by a quarter of a second).

To cleanse data from non-systematic outliers, several types of data were excluded from the sample:

- recordings marked as noise by experts;
- areas of normal sinus rhythm, on which rare episodes of violations such as extrasystoles are found;
- fragments marked Q (unclassified beat), U (ECG not readable), I (isolated QRS-like artifact).

Within the rhythm with a driver, normal beats are also allowed due to the recording features that smooth out the leading edge of the beat: tape recording, frequency response distortions, and others.

Next, a set of intervals is formed containing a single rhythm, the length of which is a multiple of a second and not less than 10 seconds. Final validation data that should not overlap with the training set is separated from the sample under study. The amount of test data is defined as 10% of the amount of training data. To generate the required number of samples, the data must be multiplied.

Rhythm	Files	Parts	Seconds	Pieces	PieTst	Test	Shifts	Learn
N	33	603	36731	3427	2824	10	0	3417
AFIB	8	77	7392	706	629	10	0	696
P	2	68	2516	227	159	10	0	217
SBR	1	10	1567	152	142	10	0	142
B	6	40	1443	127	87	10	0	117
T	7	36	819	72	36	7	1	164
BII	1	5	698	68	63	7	3	115
AFL	3	17	538	48	31	5	1	101
PREX	1	19	415	35	16	4	2	161
SVTA	3	5	141	12	7	1	5	116
VFL	1	4	132	12	8	1	8	107
IVR	2	2	130	12	10	1	9	101
AB	1	2	80	7	5	1	10	106
VT	1	2	74	6	4	1	7	103
NOD	2	5	73	6	1	1	8	109

Table 1. presents the distribution of the prepared data by grade

Rhythm: A label for this rhythm in standard annotations.

Files: The number of files in which this rhythm occurs.

Parts: Number of original intervals (at least 10 seconds long, divisible by a second).

Seconds: The total length of Parts in seconds (in descending order).

Pieces: The number of non-overlapping 10-second intervals into which the Parts can be sliced (sum of lengths divided entirely by 10).

PieTst: Parts lasting 20 seconds or more can give (Len // 10 - 1) Pieces for testing. In this case, there will be no lost residues shorter than 10 seconds.

Test: The number of legs for the final test. Minimum of three numbers:

- 10% Pieces, rounded to the nearest whole;
- PieTst (we can cut as much as possible without small residues);
- 10% of the ordered number of items in the class.

Shifts: The number of steps required for overlapping windows per second to get windows is slightly more than ordered for elements of this class. If = 0, then choose from non-overlapping Pieces.

Learn: The number of resulting bins, which is further decimated until the specified number of class elements is reached.

All work on the preparation of the training and test sample was carried out not with the data itself, but with the records containing the counting number of the beginning of the fragment and the duration in seconds. Based on the prepared indices of these fragments, the data is extracted and subjected to the simplest preprocessing: subtraction of the constant component. Additionally, each element is present in inverted form to operate with inverse electrode stacking (record 114). Therefore, the actual amount of data is doubled.

After training and testing the DCNN network, the following results were obtained:

Classification report					Confusion matrix							
Pre-cision	recall	F1-score	Sup-port	rhythm	N	AFIB	P	SBR	B	T	BII	AFL
0.91	1.00	0.95	20	N	20	0	0	0	0	0	0	0
0.87	1.00	0.93	20	AFIB	0	20	0	0	0	0	0	0
1.00	1.00	1.00	20	P	0	0	20	0	0	0	0	0
1.00	1.00	1.00	20	SBR	0	0	0	20	0	0	0	0
0.95	1.00	0.98	20	B	0	0	0	0	20	0	0	0
1.00	0.86	0.92	14	T	0	2	0	0	0	12	0	0
1.00	1.00	1.00	14	BII	0	0	0	0	0	0	14	0
1.00	0.90	0.95	10	AFL	0	1	0	0	0	0	0	9
1.00	1.00	1.00	8	PREX	0	0	0	0	0	0	0	0
1.00	1.00	1.00	2	SVT	0	0	0	0	0	0	0	0
1.00	1.00	1.00	2	VFL	0	0	0	0	0	0	0	0
1.00	1.00	1.00	2	IVR	0	0	0	0	0	0	0	0

0.00	0.00	0.00	2	NOD	2	0	0	0	0	0	0	0

0.96			158	Accuracy
0.85	0.85	0.85	15	Macro average
0.94	0.96	0.95	158	Weighted average
0.968				Ranking-based average

Table 3. Four grades with good results

It is easy to see that the neural network is subject to pronounced overfitting for classes with a small training sample: T, AFL, SVTA.

For the remaining 4 grades, it makes sense to re-do the learning and validation process. Validation results are marginally better for 3 grades. Presumably, as a result of cleaning the training sample from noise by small classes:

Classification report					Confusion matrix				
Pre-cision	recall	F1-score	Sup-port	rhythm	N	AFIB	P	B	P
0.93	1.00	0.97	154	N	154	0	0	0	0
0.93	0.92	0.92	126	AFIB	00	116	0	0	0
1.00	1.00	0.76	26	B	1	9	20	16	0
1.00	1.00	1.00	290	P	0	0	0	0	290
0.97			596	Accuracy					
0.97	0.88	0.81	596	Macro average					
0.97	0.97	0.96	596	Weighted average					
0.983				Ranking-based average					

Table 4. Validation results of the remaining four classes

From the studies carried out, it can be concluded that even 2-3 patients' records may be sufficient for reliable recognition of heart rhythm pathologies. The quality of such models should be checked in practice with the obligatory selection of a group of patients for validation. It seems that the amount of data required for each case depends on the characteristics of rhythm disturbances inherent in one or another pathology.

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