Development of Neural Network-Based Approach for QRS Segmentation

Anna Borde, George Kolokolnikov
Medicom LLC
Moscow, Russia
115@medicom77.ru, geokolok@medicom77.ru

Victor Skuratov
All-Russian Research Institute of Radio Engineering
Moscow, Russia
viktor.skuratov@gmail.com

***Abstract*—The paper is devoted to the development of QRS segmentation system based on deep learning approach. The considered segmentation problem plays an important role in the automatic analysis of heart rhythms, which makes it possible to identify life-threatening pathologies. The main goal of the research is to choose the best segmentation pipeline in terms of accuracy and time-efficiency. Process of ECG-signal analysis is descripted and the problem of QRS segmentation is discussed. State-of-the-art algorithms are analyzed in literature review section and the most prominent are chosen for further research. In the course of the research three hypotheses about appropriate deep learning model are checked: LSTM-based model, 2-input 1-dimensional CNN model, and "signal-to-picture" approach based on 2-dimensional CNN. All the architectures are tested, and their advantages and disadvantages are discussed. The proposed ECG segmentation pipeline is developed for Holter monitor software.**

I. Introduction

Diagnosis of patients with cardiovascular diseases (CVD) has now become easier thanks to advances in Holter monitoring (HM) — the monitoring of the electrical activity of the cardiovascular system for at least 24 hours. However, death rate from CVD globally increased over the last 10 years by 14.5% and amounted nearly 17.6 million deaths in 2016 [1]. Solution to this problem requires improvement in automatic ECG interpretation algorithms for HM analysis software.

One of the most important tasks in automatic ECG signal analysis is detection specific points of P, QRS and T waves, i.e. ECG segmentation. Specific points include onset, peak and offset of each wave (Fig. 1).

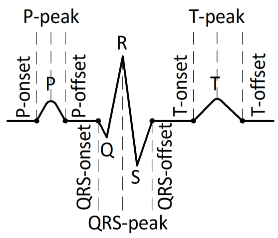

Fig. 1. Specific points of ECG signal wave

ECG segmentation can be performed by classical mathematical methods, including such algorithms as heuristic rules and probabilistic models [2]. However, these approaches require large computing resources in cases of very noisy signals and various morphologies of ECG signal waves. Deep learning models, especially artificial neural networks (ANN), are currently the most promising way to overcome these limitations [3].

Clinical conditions of HM ECG analysis software use are strictly time limited due to high patients' flow. In this connection, the main criterion for choosing the ANN architecture along with accuracy maximization is inference time minimization. The research discusses one software module for ECG analysis that solves the problem of ECG waves segmentation. The entire Holter ECG signal analysis pipeline is shown in Fig. 2.

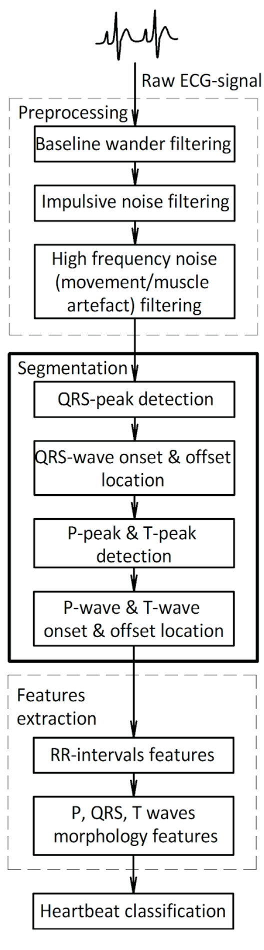

Fig. 2. Holter ECG signal analysis pipeline (module, developing in the paper, is highlighted with solid bold lines, other modules – with dashed lines)

II. Goal setting and development pipeline

The development of QRS segmentation system goes through the steps shown in Fig. 3. The research is aimed to define the most precise signal segmentation algorithm with the least computing power consumption.

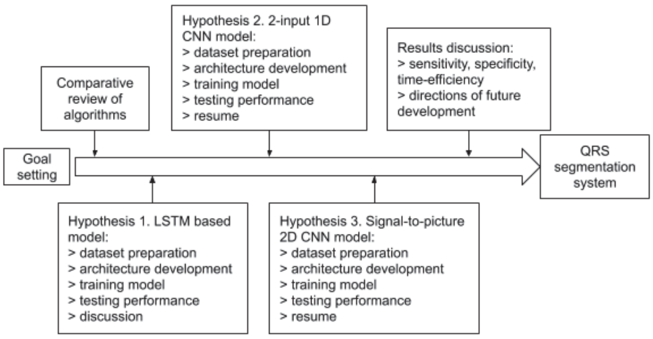

Fig. 3. Development pipeline

At the first step, comparative study of modern algorithms is conducted. Then the first hypothesis is checked: LSTM-based model with pre- and post-processing operations is developed and dataset for training is formed. After training the model, testing takes place. According to the acquired results, the hypothesis about the applicability of the approach is accepted or rejected. At the next stage, the same sequence of operations is applied to the 2nd hypothesis about 2-input 1-dimensional convolutional neural network model. Finally, hypothesis 3 about "signal-to-picture" approach based on 2-dimensional convolutional model is checked. After aggregating the performance characteristics of each method, the best approach is defined, and directions of model development are discussed.

III. Literature review

A. Standard evaluation procedure of QRS detection algorithms

According to IEC 60601-2-47:2012 (Medical electrical equipment - Part 2-47: Particular requirements for the basic safety and essential performance of ambulatory electrocardiographic systems) for a reliable evaluation of the algorithm, the sensitivity and specificity of heartbeat detection should be presented. Evaluation indexes are the sensitivity (Sen) and positive predictivity (PPR) [4], which are defined as follows:

$$Sens = \frac{TP}{TP+FN} \times 100\%$$
$$PPR = \frac{TP}{TP+FP} \times 100\% \qquad (1)$$

where TP is the number of truly detected QRS complexes, FN is the number of false negative (missed detected) QRS complexes, and FP is the number of false positive (extra falsely detected) QRS complexes.

A large number of ECG databases (DB) with annotated ECG records is available on the PhysioNet Resource [5]. For evaluation procedure AHA, MIT-BIH, NST, CU and ESC DB are recommended [4]. For segmentation algorithms evaluation QTDB is also commonly used [6]. QTDB provides onset, peak, and offset markers for P, QRS and T waves.

B. Comparison of existing ANN-based approaches

According to the literature review of ECG specific points detection algorithms in the last 10 years, there is a prevalence of ANN-based approaches over classical mathematical methods [7]. Due to the huge number of such publications we limit our review by the results of working groups published since 2018. Evaluation results of ANN-based approaches are presented in Table I. Terms and definitions used in Table I: CNN – convolution neural network; LSTM – long short-term memory; MLP – multilayer perceptron; RNN – recurrent neural network.

TABLE I. Comparison of ANN-based approaches published since 2018

Authors	ANN architecture	ECG DB	Sen	PPR	Explanations
Xiang Y., Lin Z., Meng J.	2-input 1-D CNN [3]	MIT-BIH	99.86%	99.89%	QRS-peak detection of raw ECG and with noise added
Jun T. J., Nguyen H. M., Kang D., Kim D., Kim D., Kim Y. H	2-D CNN [8]	MIT-BIH	97.85%	98.55%	QRS-peak detection and heartbeat classification
Abrishami H., Han C., Zhou X., Campbell M., Czosek R.	Bidirectional RNN with LSTM layers [9]	QTDB	95.00%* 98.00%** 97.00%***	–	Segmentation of P, QRS and T waves (* - P segmentation, ** - QRS segmentation, *** - T segmentation; accuracy for all waves is given instead of Sen)
Yildirim Ö.	Bidirectional RNN with LSTM layers and additional wavelet-based layer [10]	MIT-BIH	99.39%	–	QRS-peak detection and heartbeat classification
Saadatnejad S., Oveisi M., Hashemi M.	Multiple RNN with LSTM layers and wavelet transform features [11]	MIT-BIH	93.00%* 66.90%**	98.20%* 95.70%**	QRS-peak detection and heartbeat classification (* - results for ventricular ectopic beats, ** - results for supraventricular ectopic beats)

Full segmentation pipeline by LSTM neural network is presented only in work [9]. The results are lower than in 1-D CNN approach [3], however this approach focuses only on the peak detection. A detailed review on classical mathematical methods for ECG segmentation is presented in [2] and reports that methods based on the wavelet transform are the most promising. Thereby researches [10] and [11] using discrete wavelet transform (DWT) features are interesting in terms of increasing the accuracy of ANN-based algorithms work.

IV. MATERIALS AND METHODS

A. Technological stack and datasets

Technological stack used in the research is based on Python 3.6 programming language [12] with utilization of the following libraries:

- Pandas [13] – for data management.
- Scikit-learn [14] – for dataset preparation.
- WFDB [15] – for reading, writing, and processing PhysioNet signals and annotations.
- SciPy [16] – for ECG-signal processing.
- Keras with TensorFlow backend [17] – for deep learning model training and testing.
- Auxiliary packages like Numpy [18], Matplotlib [19], etc.

The development of segmentation systems is carried out with the following hardware:

- Nvidia GeForce GT 1030 GPU for prototyping and testing models.
- Google Colaboratory with Tesla K80 GPU for training.

The following databases are used in the research:

- QTDB [6] – a database for evaluation of algorithms for measurement of QT and other waveform intervals in the ECG.
- MIT-BIH Arrhythmia database [20] – a database with 48 half-hour excerpts of two-channel ambulatory ECG recordings.

The QTDB contains a total of 105 fifteen-minute two-lead ECG records (many excerpted from other databases), with onset, peak, and offset markers for P, QRS, T, and (where present) U waves of from 30 to 50 selected beats in each record. Description of the MIT-BIH Arrhythmia DB is presented in Table II.

TABLE II. DESCRIPTION OF THE MIT-BIH ARRHYTHMIA DB

ECG DB	Record ID	Description	Records number
MIT-BIH	100, 101, 103, 105, 106, 108, 109, 111-119, 121-124	Records without arrhythmia	20
	200-203, 205, 207-210, 212-215, 219-223, 228, 230-234	Records with arrhythmia	24
	Total records number		44
	102, 104, 107, 217 Records contain impulses of an artificial pacemaker, excluded		4

Each record of QTDB is preprocessed according to the algorithm shown in Fig. 4 and saved as CSV database. The similar preprocessing pipeline is applied to records of MIT-BIH database (Fig. 5). In each studied method datasets are preprocessed additionally in a specific way, depending on the used neural network architecture, to form training and testing datasets.

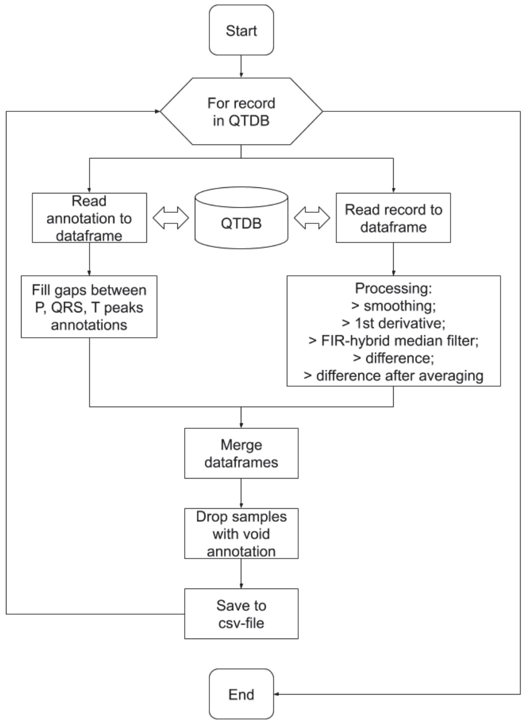

Fig. 4. Algorithm of QTDB preprocessing

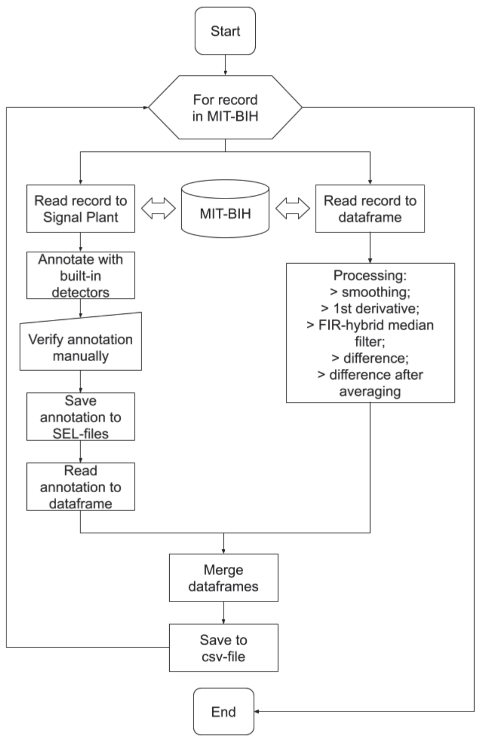

Fig. 5. Algorithm of MIT-BIH preprocessing

B. Hypothesis 1: LSTM-based model

The first method is based on a bidirectional long short-term memory (BLSTM) neural network [21]. This type of recurrent neural network is well-known for high performance while working with time-domain signals and sequential data. It allows to reach previous and future input information from the current state, so the context of the input helps to distinguish different classes. It is useful in ECG analysis as the signal has periodical trend: QRS complex goes after P wave and is followed by T wave. The proposed implementation of network is working in many-to-many sequence classification mode. The model is trained to detect P, QRS, and T waves.

The signal segmentation pipeline based on the BLSTM model is shown in Fig. 6. The initial signal is preprocessed (smoothed, filtered, or differentiated). Then 250-samples window is moving along the signal. This window is given to LSTM network which generates 250 labels of annotation. After the signal analysis is done, generated annotation is subjected to median filtering that removes wrong spikes (dramatic changes in annotation). Additional logic filter controls the correct sequence of P, QRS, and T waves. Median filter window size is chosen according to information about ECG waveforms possible duration: both normal and abnormal (Table III – information provided by Department of Therapeutic faculty, Pediatric faculty, Russian National Research Medical University named after N.I. Pirogov RNRMU). For avoiding QRS false positive detection according to minimum QRS width in MIT-BIH DB window size is chosen equal to 23.

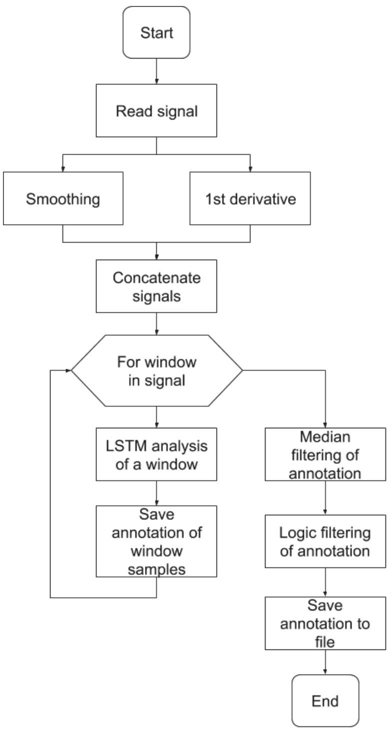

Fig. 6. Signal segmentation pipeline based on the BLSTM model

TABLE III. ECG WAVEFORMS DURATION

ECG feature	Duration, ms	Duration (fs = 360 Hz)
P width	30-200	10-72
PQ interval	80-400	28-144
QRS width	50-240	18-87
QT interval	200-700	72-252
T width	30-240	10-87

The architecture of bidirectional long short-term memory network is inspired by paper [9] (Fig. 7) and consists of two bidirectional LSTM layers and one time distributed dense layer.

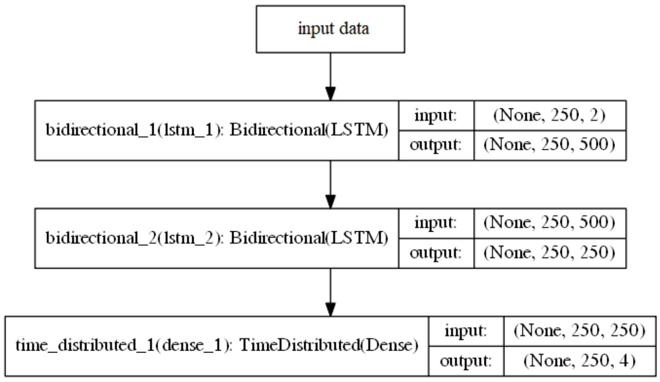

Fig. 7. Architecture of BLSTM neural network

The BLSTM network requires specific input data form: it can process at one time number of samples that is equal to the number of input neurons. It can also get time-dependent signal with more than one feature in one sample. This means that the BLSTM can get filtered, differentiated or smoothed signal along with the initial one as input. Consequently, the input data size is (windows size x number of features per sample). To form dataset for BLSTM, each record of QTDB in csv-format is split into segments of 250-samples length. The total number of signal segments in training set is 2900 and 350 in testing set.

The BLSTM model is trained for 200 epochs with batch size of 64 signal segments. Categorical cross entropy is chosen as loss function and Adam method for optimization. After 15 epochs learning curves go to a plateau. The learning curves for the BLSTM model with smoothed and differentiated signals as input are shown in Fig. 8.

The proposed pipeline requires approximately 0.40 second to process 1 second of signal with 250 Hz sampling frequency. Example of signal segmented with trained BLSTM is shown in Fig. 9. The lower curve is ECG signal and the upper – annotation (0 stands for “neutral”, 1 – “P”, 2 – “QRS”, 3 – “T”). The segmented signal has many wrong detections, which can be removed by median and logic filtering (Fig. 10). Although the pipeline manages to locate complexes, the accuracy of edge detection is not very high. Moreover, the method is not time-efficient, thus, it is declined.

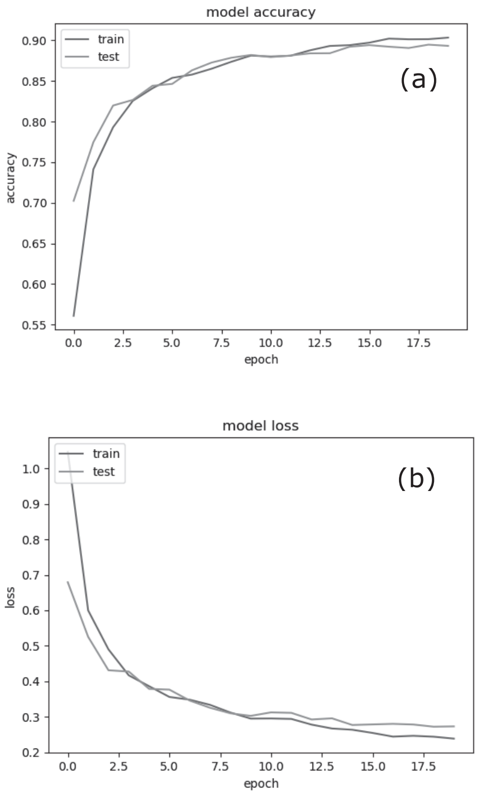

Fig. 8. Learning curves for BLSTM network: (a) accuracy learning curve, (b) loss learning curve

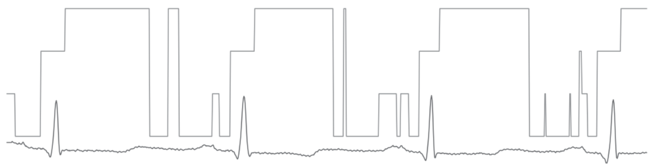

Fig. 9. BLSTM-segmented signal before filtering

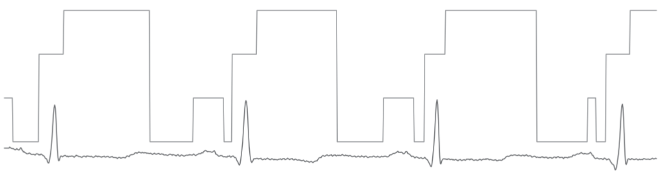

Fig. 10. BLSTM-segmented signal after median and logic filtering

C. Hypothesis 2: 2-input 1-D CNN-based model

As ECG signal is a time sequence, using 1-D variation of CNN models seems to be the most suitable processing method. This method is based on the idea of classification a current signal count into 4 classes: P-wave, QRS-wave, T-wave or neutral (baseline). The central count of a window is classified according to the surrounding context.

The signal segmentation pipeline based on the 2-input 1-D CNN model is shown in Fig. 11. The initial signal is preprocessed (differentiated and differentiated after averaging). Then 250-samples window is moving along the signal and the 125th count of a current window is classified according to neighbor counts. After the signal analysis is done, generated annotation is subjected to median filtering that removes wrong spikes, as in hypothesis 1.

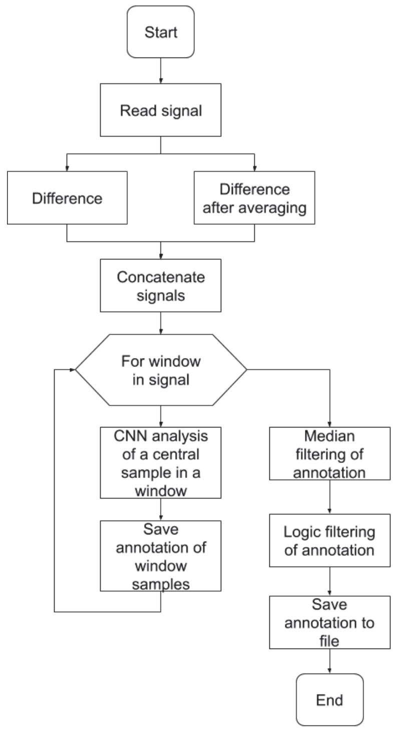

Fig. 11. Signal segmentation pipeline based on the 2-input 1-D CNN model

The architecture of 2-input convolution neural network is inspired by paper [3] (Fig. 12). Differentiated signal is given as the first input and differentiated after averaging signal as the second input of the neural network. The first branch of the network is represented by two convolutional layers, whereas the second one contains one conv layer. Features extracted by two convolutional branches are concatenated and passed to fully connected classification layers. Fig. 12 shows the variation of the architecture developed only for QRS segmentation: it annotates signal in 1 for QRS and 0 for non-QRS segment. That is why the last layer consists of 2 neurons.

2-input 1-D CNN model gets 250-sample frames as input, so the dataset should be processed to fit the input size: number of frames x window size x feature per sample. For instance, record containing 650000 samples is split into 649750 frames (record length minus frame length).

The method under consideration turned out to be demanding on a large amount of data. To generate additional training set, QRS onset and offset annotation of downsampled MIT-BIH DB with 250-Hz frequency is carried out using SignalPlant, an open signal processing software platform [22]. QRS complexes edges are obtained with SignalPlant built-in detector and then manually verified. Thus, training set consists of QTDB and MIT-BIH DB records.

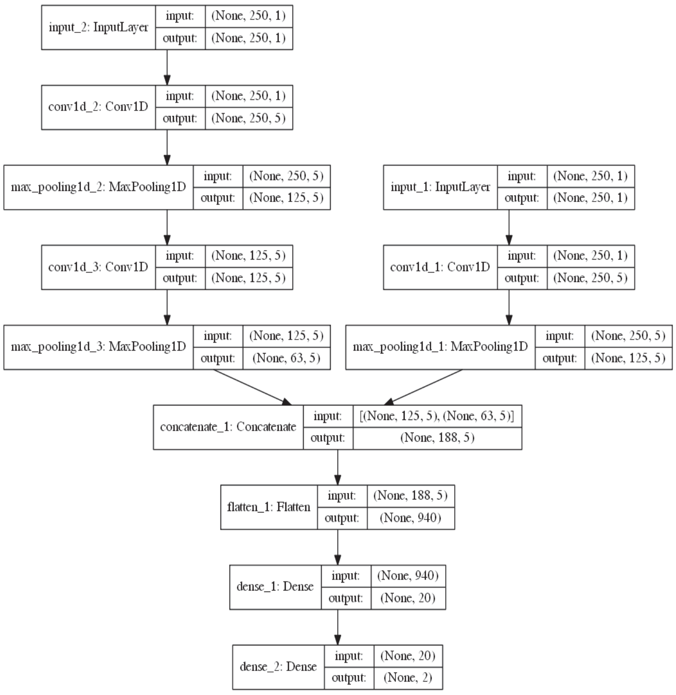

Fig. 12. Architecture of 2-input 1-D CNN

The model is trained for 100 epochs with batch size of 128 frames. Categorical cross entropy is chosen as loss function and Adam method for optimization.

Validation of the signal segmentation pipeline is conducted on MIT-BIH DB (360 Hz). The results of performance evaluation are shown in Table IV. Fig. 13 shows QRS segmentation after median and logic filtering. As follows from the table and figure, method based on the 2-input 1-D CNN model performs high accuracy of both peaks and edges detection. Nevertheless, the method requires approximately 0.45 second to process 1 second of signal with 360 Hz sampling frequency, so it is not time-efficient enough for real-world applications.

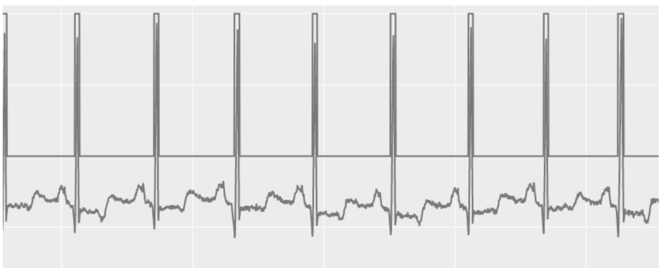

Fig. 13. 2-input 1-D CNN QRS segmentation after median and logic filtering

D. Hypothesis 3: 2-D CNN-model

So called “signal-to-picture” approach is based on converting 1-D signal into 2-D image and its classification with simple CNN. The main intuitions of this method are in the following:

- Cardiologist’s visual analysis analogy: segmentation system is “looking through” the signal, finds QRS peaks, and detects edges.
- CNN architecture is originally intended for image analysis.
- The proposed method uses the simplest CNN models to increase time-efficiency.
- System uses two CNN models: one for QRS peak detection, another for QRS edges detection.

TABLE IV. PERFORMANCE EVALUATION OF THE HYPOTHESIS 2 USING THE MIT-BIH DB

Record	Total beats	TP	FP	FN	Sen, %	PPR, %
100	2273	2270	0	3	99.87	100.00
101	1856	1850	4	6	99.68	99.78
103	2084	2082	2	2	99.90	99.90
105	2572	2524	84	48	98.13	96.78
106	2027	2017	20	10	99.51	99.02
108	1763	1682	36	81	95.41	97.90
109	2532	2519	10	13	99.49	99.60
111	2124	2093	3	31	98.54	99.86
112	2539	2517	4	22	99.13	99.84
113	1795	1784	114	11	99.39	93.99
114	1879	1874	1	5	99.73	99.95
115	1953	1951	1	2	99.90	99.95
116	2412	2391	3	21	99.13	99.87
117	1535	1533	1	2	99.87	99.93
118	2278	2255	28	23	98.99	98.77
119	1987	1986	11	1	99.95	99.45
121	1863	1852	14	11	99.41	99.25
122	2476	2472	0	4	99.84	100.00
123	1518	1516	4	2	99.87	99.74
124	1619	1617	14	2	99.88	99.14
200	2601	2573	37	28	98.92	98.58
201	1963	1961	1	2	99.90	99.95
202	2136	2134	20	2	99.91	99.07
203	2980	2893	34	87	97.08	98.84
205	2656	2653	0	3	99.89	100.00
207	1860	1844	232	16	99.14	88.82
208	2955	2935	3	20	99.32	99.90
209	3005	2982	1	23	99.23	99.90
210	2650	2631	9	19	99.28	99.66
212	2748	2717	0	31	98.87	100.00
213	3251	3248	0	3	99.91	100.00
214	2262	2242	196	20	99.12	91.96
215	3363	3358	2	5	99.85	99.94
219	2154	2153	18	1	99.95	99.17
220	2048	2045	1	3	99.85	99.95
221	2427	2422	4	5	99.79	99.84
222	2483	2469	8	14	99.44	99.68
223	2605	2597	28	8	99.69	98.93
228	2053	2012	44	41	98.00	97.86
230	2256	2253	6	3	99.87	99.73
231	1571	1570	3	1	99.94	99.81
232	1780	1776	12	4	99.78	99.33
233	3079	3075	4	4	99.87	99.87
234	2753	2752	0	1	99.96	100.00
Overall	100724	100080	1017	644	99.36	98.99

The pipeline of “signal-to-picture” approach is shown in Fig. 14. The ECG signal is scaled and transformed into a set of ECG images with 75x150 size where the number of samples is plotted on one axis, and the normalized signal amplitude on the other. Each image is the result of 75-samples window moving along the initial signal with a sequential 1-sample shift. After transformation, image data is sent to CNN for analysis to determine the position of the QRS complex, after which its maximum is determined. Further, in a certain area around the maximum obtained, a "window" of variable duration is run, and the received images are sent for analysis to the second CNN, which acts as an edges detector of QRS complexes. According to the frame selected by CNN, the QRS complex onset and offset are located. The annotation of the signal containing QRS onset, peak, and offset is saved to a file. The developed system is trained to detect QRS peak, onset and offset.

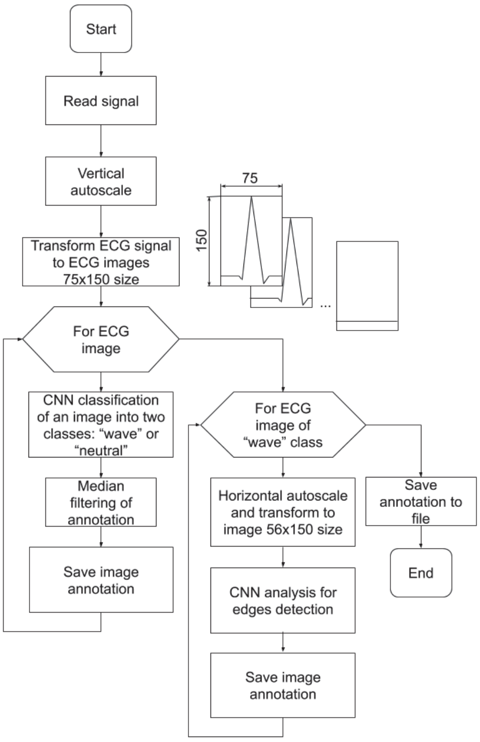

Fig. 14. Signal segmentation pipeline based on 2-D CNN model

We used two CNN of the same architecture with difference in the last layer. Fig. 15 shows CNN model for peak detection.

Two datasets are required to train CNN models used in "signal-to-picture" approach. The datasets are formed from selected MIT-BIH records. The first set contains "wave" and "non-wave" classes. "Wave" class has instances in which QRS peak is located in the middle of the image. All the other images with non-QRS waves or with QRS peaks shifted from the center position belong to "Non-wave" class. The second dataset consists of images with QRS peaks located in the middle but with different onset and offset location. There are two classes in this set: "Correct" and "Incorrect" edge location.

Training process of each neural network takes 20 epochs. Accuracy on test set is more than 0.99 in the of the training process. The proposed pipeline can process 1 second of MIT-BIH record with 360 Hz in 0.03 second. Results of ECG signal segmentation are demonstrated in Fig. 16.

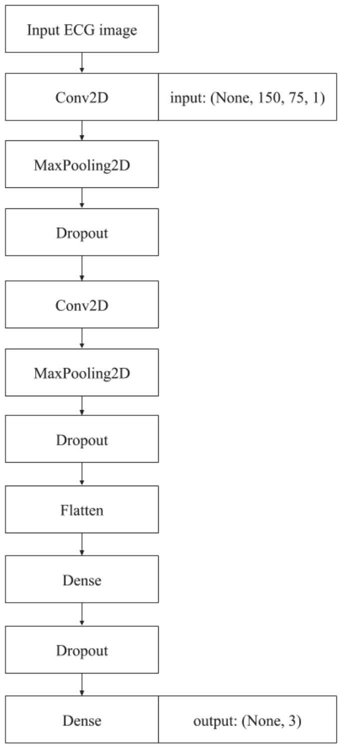

Fig. 15. Architecture of CNN for QRS peak detection

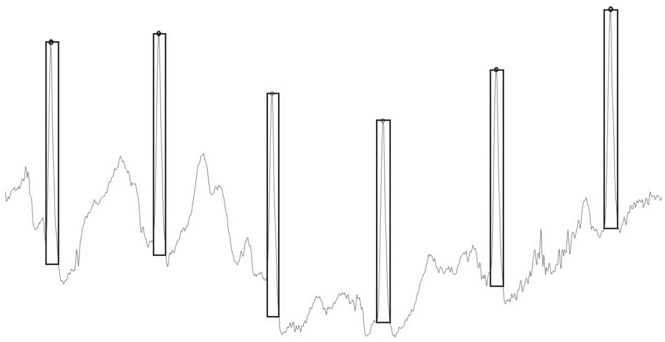

Fig. 16. ECG segmentation by "signal-to-picture" approach

The "signal-to-picture" approach is still under evaluation, but performance of the system is limited by accuracy characteristics of its modules, therefore, the proposed method is able to provide the highest accuracy results with lowest computing power consumption among the considered hypotheses.

V. Results and Discussion

According to models' evaluation results, the most time-efficient method of QRS segmentation is "signal-to-picture" 2-D CNN approach. Moreover, it gives sufficient accuracy which is comparable to 2-input 1-D CNN model. The latter has significant computing power consumption that is not the case for real application in Holter ECG signal analysis system. The results of models' evaluation are shown in Table V. The

BLSTM-based method satisfies neither in accuracy nor in time-efficiency.

TABLE V. COMPARISON OF THE TWO MOST SUITABLE APPROACHES

Model	Average accuracy, %	Time required for analysis of 1 second of 360 Hz ECG record, seconds
2-input 1-D CNN model	99.18	0.45
2-D CNN model	99.00	0.03

The further directions of QRS segmentation system development include:

- Development of both P and T waves detection modules with the selected approach.
- Combining "signal-to-picture" approach for QRS peaks detection with LSTM-based method for targeted P, QRS and T edges detection (applying LSTM network only to QRS peak area).
- Improving time-efficiency with code base conversion to C++ and parallel programming.

VI. CONCLUSION

In the course of the research devoted to the development of automated QRS segmentation system, we have carried out literature review to define approaches with the highest performance characteristics. Three hypotheses about ECG segmentation methods are checked and the best one is accepted. Detailed description of dataset preparation, algorithm architecture and training the model is provided for each approach. BLSTM-based model is built and tested, but evaluation shows the impossibility of applying the model in real-life applications. 2-input 1-D CNN model has demonstrated high accuracy of peak and edges detection – average accuracy is 99.18%, but long processing time – it takes 0.45 seconds to process 1 second of 360 Hz MIT DB ECG record. Finally, "signal-to-picture" approach has proved its efficiency in terms of accuracy – 99% which is close to the results of the previous approach, and time-efficiency – the proposed algorithm is 15 times faster than the previous one. Although it seems to be the most appropriate approach for QRS segmentation, it has one major disadvantage which is data preprocessing step. ECG signal registered in time domain form needs to be transformed into 2-D data, in turn it leads to time and computing power consumption at the data preparation step. In spite of that, 2-D CNN "signal-to-picture" method is chosen for further improvement and is expected to be deployed into Holter ECG signal analysis pipeline.

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