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A complete system for an automated ECG diagnosis

***Abstract**. We present a very simple LSTM neural network capable of categorizing heart diseases from the ECG signal. With the use of the ECG simulator we ware able to obtain a large data-set of ECG signal for different diseases that was used for neural network training and validation.*

***Streszczenie.** W artykule prezentujemy bardzo prostą sieć LSTM zdolną do rozpoznawania jednostek chorobowych przy chorobach serca. Dodatkowo pokazujemy w jaki sposób stworzyliśmy bazę danych sygnałów pomiarowych użytych do nauki i walidacji sieci neuronowej przy użyciu symulatora EKG. (**Kompletny system do zautomatyzowanej diagnozy EKG**).*

Keywords: Neural networks, LSTM, ECG
Słowa kluczowe: Sieci neuronowe, LSTM, EKG

Introduction

According to the world health organization statistics, myocardial disorders is responsible for 31% of world deaths. As a consequence of that the research centers specialized in medical data processing are trying to create systems for the analysis of ECG signals. The idea of these type of systems is to automatically detect possible threats in ECG and notify the appropriate medical units. In the paper we present a complete system for measuring and analysis of ECG signal. It consist of our own measuring hardware and an AI based diagnosis system that is able to detect life-threatening heart disorders.

With the use of artificial intelligence methods, we can find and assign the appropriate ECG fragment to a given heart disorder. Additionally, the system has ability to automatically detect and mark an unknown data segments in ECG. This kind of system for analyzing ECG signals allows for faster diagnosis and thus increase the chance for appropriate treatment of the patient.

There have been many attempts for solving optimization problems [1-22] and training and use neural networks (NN) to diagnose heart diseases.

In the paper by Ribeiro et al. [23] the deep neural network was used to classify a 12-lead ECG. They ware able to achieve a very high accuracy with over 80% F1 score, and specificity over 99%. The authors used a 400 Hz sampling rate for the ECG signal, and the samples were sliced between 7 and 10 s. The downside of their method is that they used a very complex model of a deep neural network with large number of layers; with max pooling along with the convolution layers. As the results is impressive it is surprising that the authors did not used recurrent neural networks (RNN) for this task, as it could greatly simplify the structure of the network.

El-Khafif et al. [24] used a classical multilayered neural network for their work. With the use of publicly available data they where able to train the neural network and achieve accuracy of 93%. The samples where gathered from only two channels and were digitized at 250 Hz. Here authors also did not used RNN. It is worth noting that rather simple neural networks models were used, which has a big upside in term of reconstruction of the results obtained in this paper.

Li et al. [25] used convolutional neural networks in their work. This approach while somewhat similar to the Ribeiro et al., differs in the fact, that the structure of the used CNN is much simpler. Also the multi-layer CNN was used by Ribeiro et al., while Li et al. used a simpler algorithm involving CNN. The result of this work is a CNN with accuracy of over 99.1%. The ECG signals were translated to the 2D image via one-hot encoding in order to improve its accuracy and convergence speed. Here authors also did not used RNN which are best suited for tasks involving time depended signals.

In this paper we present, simple, yet robust neural network that capable to diagnose heart diseases. We used a RNN which uses LSTM cells that are excellent choice while dealing with time depended data.

Methods

To properly teach a neural network we needed the right amount of data. One source of the data could be publicly available database such as physionet.org. Unfortunately to properly train the neural network one need to have over 10000 samples of each heart disease properly tagged. This makes the data-set very large and exhaustive. Due to the lack of publicly available database that would fulfill the requirements, we decided to build our own database.

In order to gather such a large amount of ECG data, an innovative ECG measuring device was used.

As a heart of the ECG measuring system we used a chip manufactured by Texas Instruments with catalog note ADS1298. To generate data we used the ECG simulator from FLUKE model ProSim 4, which has 10 leads.

The simulator has the ability to simulate arterial pressure in the range of 0 mmHg, 80 mmHg, 160 mmHg and 250 mmHg. It is also capable of simualting varois heart diseases.

The ProSim 4 Life Signs Simulator, equipped with a large touch screen display, is designed to quickly check patient monitors directly at the point of use. Easy and secure connection makes the simulator test 12-lead ECG, NIBP, IBP and breathing in seconds.

Built-in test sequences, intuitive operation and access to most functions with a single touch of the screen make ProSim 4 an irreplaceable diagnostic tool for evaluating the performance of monitoring devices.

Mean futures of the FLUKE divice includes:

- Accurate, reproducible simulations of ECG, NIBP, IBP and respiration
- Repeatable NIBP simulation (+/- 2 mmHg) for dynamic pressure repeatability testing
- Standard electronic pressure gauge
- Light and handy
- Access to most functions with one touch of the screen
- Integrated, easily replaceable battery with a long operating time
- Intuitive, multilingual user interface

The combination of the FLUKE ProSim4 device together with our ECG system was used to collect as close to real life ECG data is possible which is essential to be able to properly train neural network.

The neural network

The neural network used in this paper consisted of 7 layers. The final configuration was a result of intensive testing of different structures of networks.

First we started with a simple structure with dense layers. Then started to modify the network with the use of BILSTM layers. Each combination was trained with the same set of the data and is performance was compared. The final structure is described in table 1.

In the network we used Long Short Term Memory (LSTM) cells which has proved to be effective in solving a wide range of cognitive learning tasks. Speech and handwriting recognition, and more recently machine translations are the most prevalent in the literature. It is well known that this kind of neural network has a good performance when feed with images [26-29].

The idea of of RNN in general is that it is able to track arbitrary long-term dependencies in the input sequences. The LSTM enhances this idea by introduction forget gate which mimics the short term memory.

The lack of the possibility to process already processed information seems to be the main disadvantage of ordinary neural networks (Muli-layer Perceprton or feed-forward network). It is unclear, for example, how a network could make sense of an upcoming sentence or word without context, both in terms of natural language processing and acoustic speech recognition. The same applies to other non-stationary signals. In contrast, RNNs are able to remember processed information and use it in the current learning moment.

All cells in RNN networks have a form of iteration that can be repeated. In a basic RNN cell, each iteration relay is taken by a simple structure, for example, by the tanh function.

LSTN has the ability to add, add and subtract information from its current state. The sigmoid function determines how much of the previous and present information is to be transmitted for further processing.

Such networks are currently considered the most promising tool for analyzing sequences, including time series. Unfortunately, due to the high computational complexity and the number of hyperparameters, building an optimal network can be extremely time consuming, especially with a large amount of analyzed data. Promising results bring simplification of the LSTM neuron by leaving only the input gateway and memory control (so-called Gated Recurrent Unit - GRU), so that the memorized information is passed on to further neurons at each iteration. Reducing the number of "switches" reduces the need for computing power during network training at the expense of reducing the accuracy of the pattern memorized by the network.

The main building block of the LSTM is a memory cell, which is represented by a hidden layer in a recursive neural network. LSTM block recursive networks are called LSTM networks. Many people have worked on improving the original LSTM concept for several years, the results of the improvements are described in In addition to the original authors, and lot of people contributed to the modern LSTM.

LSTM networks are designed to avoid the problem of long-term dependency. LSTM network training allows you to remember long-term relationships between input data and output results returned by the network. The structure of an LSTM cell can resemble a computer's memory, as it can read, write and delete information using appropriate gateways. The cell decides whether to store or delete information according to the weight assigned to the information. The weights are selected in the learning process, over time the LSTM cell learns which information is important and which is not.

A traditional LSTM cell performs the following procedure:

(1) $$f_t = \sigma_g(W_f x_t + U_f h_{(t-1)} + b_f)$$

(2) $$i_t = \sigma_g(W_i x_t + U_i h_{(t-1)} + b_i)$$

(3) $$o_t = \sigma_g(W_o x_t + U_o h_{(t-1)} + b_o)$$

(4) $$c_t = f_t \circ c_{(t-1)} + i_t \circ \sigma_c(W_c x_t + U_c h_{(t-1)} + b_c)$$

(5) $$h_t = o_t \circ \sigma_h(c_t)$$

where: X_t - is the input vector, h_t - is the output vector, C_t - is a cell state vector, W and U are the matrices with weights, b is the bias vector, f_t - is a forget weigth vector, i_t is the input weight vector, O_t is output weiths vector, σ_g is a sigmoid function, σ_c is tnah function and a tnah functior or σ_h (x) = x.

The signal that we pass to the LSTM layers can be thought as a pseudo 1D images where the brightness of pixel correspond to the value of signal.

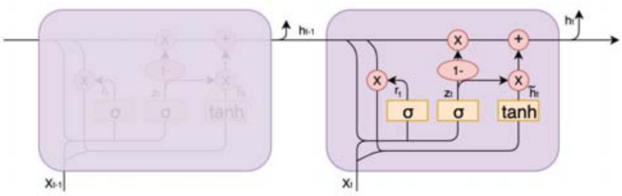

Fig.1. The structure of the LSTM cell.

The BI prefix of the BILSTM cell correlates to the feature of LSTM that the input data is passed to the network starting from first and then from the starting from last cell. This kind of learning technique is very useful in cases where the signals are periodic or quasi-periodic.

Figure 1 shows the structure of the LSTM cell while the Figure 2 shows the used ECG simulator.

Fig.2. FLUKE model ProSim 4 ECG simulator [30].

LSTM works extremely well with many different problems, that's why it was used as our solution. While the architecture of our Neural network consist of a multiple

LSTM layers, we note, that we are able to achieve 80% recognition rate with just single layer with 256 units.

All the code were written in Python with the use of Tensorflow library and the calculation were performed on the NVIDIA GEFORCE RTX 2060 graphic card.

Results and discussion

In this work we focused only on the I channel of the ECG data. The following ECG signals were collected by the system: Natural ECG signal at 60 bpm, Atrial fibrillation, Bradycardia at 30 bpm, Tachycardia at 180 bpm, Premature ventricular contraction (PVC), Ventricular tachycardia. The data was remodeled into a training an validation data sets. The data-sets consisted of a name of disorder and a 5 second sample of the disease.

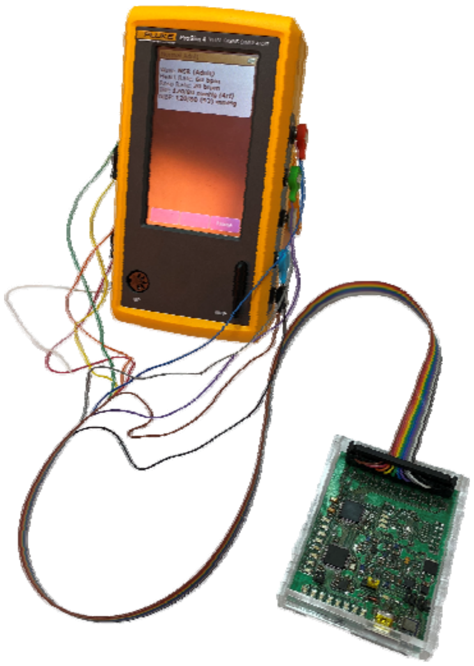

Fig.3. Our FLUKE model ProSim 4 ECG simulator with our own hardware for collecting real ECG data.

Figure 4 shows result obtained by the neural network. Each point of the upper plot is the 5 seconds of the test ECG signal. The network failed to classified only 10 out of total of 300 cases which translates to around 96% successful detection.

Table 1. The parameters of the sensor

Type	No. of units	Activation function
BILSTM	128	default
BILSTM	256	default
BILSTM	64	default
BILSTM	64	default
Dense	256	tanh
Dense	1024	sigmoid
output	6	softmax

The vast majority of articles focus their research on external databases such physionet.org [31]. In this paper we used data close to real life signal from the ECG simulator. This allowed us to create an extensive learning database for the neural network. We have shown that with the correct structure of NN we were able to achieve a high detection rate in the ECG signal.

These kind of an automated system can be used a s a part of a larger system to diagnose patient bio-signals.

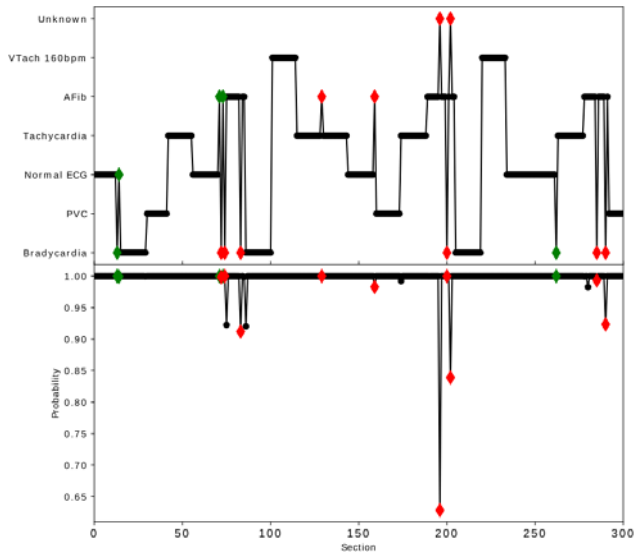

Fig.4. Results obtained with the neural network.

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