Cardiovascular Health Analysis System Using Machine Learning Model

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Abstract. Analysis of cardiovascular health is an urgent task, as the number of patients with cardiovascular diseases is growing in the world. For the early diagnosis of these diseases, various studies of the cardiovascular health of patients are used, among which the analysis of electrocardiograms (ECG) is widely used. Classifiers based on machine learning models have been developed for automatic ECG analysis. At the same time, in medical practice, the SCORE scale is often used to assess the probability of risk of cardiovascular disease, which analyzes gender, age, systolic blood pressure, total cholesterol and smoking. Therefore, this article proposes an approach and architecture for analyzing the cardiovascular health of patients that integrates automatic analysis of five types of heartbeats extracted from ECG with a linguistic assessment of the risk of cardiovascular disease on the SCORE scale. To classify heartbeats, a model based on RNN with LSTM neurons was developed, which showed an accuracy of 98.34% on the MIT-BIH Arrhythmia Database test set. A system of rules that integrates the heartbeats class and the patient's SCORE assessment was developed to provide a linguistic description of cardiovascular health, useful in forming a medical conclusion.

Keywords: Electrocardiogram, Classification, RNN, LSTM, SCORE.

1 Introduction

Diseases of the circulatory system occupy a leading place in the statistics on morbidity and mortality of the adult population in many countries, including Russia. At present, the reduction of mortality from cardiovascular diseases (CVD) is a strategic task of Russian healthcare and a key task of preventive medicine.

Informatization of health care and the use of digital technologies for data processing are priority tasks in the development of a modern information society based on knowledge in all countries. Joonseok Kim, Peter W. Groeneveld [1] note that around 2026, we may have billions of data points per person, and the real task will be to develop medical information technologies that can reduce this data to real hypotheses about human health. A number of researchers have noted the need for the use of medical data mining methods, including machine learning models [2-4] for diagnostics.

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Medical diagnostics means to the recognition of health problems, the generation and ordering of disease variants (alternatives) over a set of medical research. The result of medical diagnostics is a decision in the form of a disease class, on the basis of which a medical care plan and a linguistic assessment of the severity of CVD are formed. One of the directions of early detection of abnormalities in the functioning or developing pathology of the cardiovascular system is electrocardiography. This is a method of functional examination of the heart, based on the graphic registration of changes in time in the potential difference of its electric field (biopotentials). As a result of this study, an electrocardiogram (ECG) is formed, the analysis of which makes it possible to diagnose ischemic heart disease (IHD), acute or chronic myocardial damage; obtain information about various types of pathology (Atrial Premature Beats, Atrioventricular Block, Supraventricular premature beats, Premature ventricular contractions) [5-8].
The analysis of the ECG is based on the study of the graphic patterns of its graphic elements, such as teeth, segments and intervals, which reflect the work of the heart muscle. Changes in the size of the teeth, uneven segments indicate violations in the cardiovascular system, which requires further research and examinations, the appointment of an effective course of treatment for this patient. Although the ECG results are automatically briefly described by the electrocardiography device, they require further interpretation and description by a cardiologist due to variation in morphological and temporal characteristics of ECG waveforms. The ECG analysis process to assess the heartbeat can include more than 50 subprocesses [9], including the analysis of microalternations (primarily T-wave microalternations) [10].
From the point of view of data mining, the process of ECG analysis can be combined with an assessment of the risk of CVD by other parameters of the patient's health to form a diagnostic conclusion, and is represented by the following stages:

1) Preprocessing and segmentation of the ECG into separate sequences of the electrographic signal in each lead, which can be presented in the form of time series; In this case, each ECG lead can be represented as a one-dimensional time series, which reflects the dependence of the recorded potential difference of the electric field in the heart muscle on the moment in time.
2) Classification and description of classes of pathologies according to preprocessed ECG.
3) Summarization and interpretation of ECG with CVD risk factors for a final conclusion and recommendations to the patient.

The implementation of such process using a trained classifier model will reduce the time spent on making a medical decision, as well as reduce the number of medical errors. To achieve this goal in this paper, we propose an architecture for a CVD risk analysis system that includes an automatic linguistic interpretation of cardiovascular health, based on classification of heartbeats using recurrent neural networks and assessment of cardiovascular risk on the SCORE scale. The proposed system architecture is developed to support medical decision making.

2 Related Works in the Field of ECG Classification

Among the studies in the field of methods for the classification of ECGs, two areas can be distinguished: (1) algorithms based on morphological features and classical signal processing techniques [11-12] and (2) algorithms, used artificial neuron networks [13] - [19].

Recently, artificial neural networks (ANNs) have become increasingly popular for ECG classification due to their learning capabilities; they are more resistant to noise in the input data, which is important for ECG due to the presence of a large number of microalternations. Also, trained ANNs are able to produce results faster than other methods, which is important for emergency situations, for example, in cardiac resuscitation.

In the study by Mohammad Kachuee, Shayan Fazeli, Majid Sarrafzadeh [13], convolutional neural networks (CNN) and their modifications were used for classification of ECG beat types on the MIT-BIH arrhythmia database [14] into five classes, according to the Association for the Advancement of Medical Instrumentation (AAMI) [15], namely in short: non-ectopic (N), supraventricular ectopic (S), ventricular ectopic (V), fusion (F), and unknown (Q). A segment corresponding to one heartbeat is previously extracted from ECG signal. For this, R-peak and R-R time intervals ECG are analyzed. Thus, one heartbeat is extracted from each ECG and this data is fed to the input of the deep neural network, in the proposed architecture of which the 13 layers is used including 11 convolution layers and two fully-connected networks with 32 neurons.

In the paper U.R. Acharya, Shu Lih Oha, Yuki Hagiwara, Jen Hong Tan, Muhammad Adam, Arkadiusz Gertych, Tan Ru San [16] was described the deep learning model using a CNN for classifying the same five classes of ECGs from MIT-BIH arrhythmia database [14]. The authors use preprocessing of ECG signals by removing noise using six wavelet filters and then segmentation to search for QRS complexes of ECG signals using the algorithm presented in [17]. Each segment is normalized using a Z-Score [18] to solve the amplitude scaling problem and remove the bias effect before being fed into the CNN for training and testing. Next, the data are augmented to create a balance between the classes and transmitted to the input of CNN, which has three convolutional layers and three fully connected layers at the end to generate the output of the network.

In the study by the authors R. J. Martis, U. R. Acharya, C. M. Lim, K. Mandana, A. K. Ray, and C. Chakraborty [19] before QRS detection and segmentation, denoising of ECG based on wavelet transform was performed [20]. After that, principal components were calculated and used as features for further classification. In this study, a feedforward artificial neural network (NN) [21] and a Least-squares support-vector machine (LS-SVM) are compared in the classification accuracy of five types of ECG heartbeats on the dataset [14]. The third order correlation of the segmented signal was used to extract the subtle changes (non-leaner features) in the five kinds of ECG signals, next Principal Component Analysis was performed on the large number of cumulant coefficients, for dimensionality reduction of the features. Classification of these features is realized by feedforward artificial neural network, which contains one input layer of 12 neurons, one hidden layer of 10 neurons, and the output layer that generates the output of the network contains 5 neurons. The comparison of classification accuracy show that feedforward artificial neural network overperform the SVM in classification of ECGs.

When classifying complex data, a sequence of characters can enter the input and this sequence of characters must be recognized at the output. Often this is done using a classifier model based on a recurrent neural network (RNN) [22]. The presence of special blocks in the hidden layer NN, containing controlled elements of the «remembering / forgetting» state, is a special feature of RNN models. Currently, various configurations of recurrent neural networks based on different blocks in hidden layers are proposed, for example, BiRNN (bidirectional RNN), LSTM (RNN with long-term short-term memory), GRU (RNN with gates). The effectiveness of this kind of networks was shown in the works [23 -27].

In the paper [28], RNN Encoder-Decoder [29] is used in conjunction with CNN which extracts a sequence of heartbeat features from an ECG, the latter are then fed to the RNN Encoder-Decoder input. The Encoder encodes the heartbeat features using LSTM cells [30], while the Decoder classifies the heartbeat type. The authors of [28] use BiRNN instead of the usual RNN [31], which can process data in both forward and backward directions, in normal time order, t = 1, ..., T for the forward network, and in reverse time order, t = T, ..., 1 for the backward network. Finally, the weighted sum of the outputs of the two networks is computed as the output of the BiRNN. In this work, ECG classification is carried out for 4 classes MIT-BIH arrhythmia database [14] including N (normal and bundle branch block beats), S (supraventricular ectopic beats), V (ventricular ectopic beats), and F (fusion of N and V beats).

To better capture the patterns in the ECG waveform in paper [32], an algorithm employs both LSTM recurrent neural networks and classical features, i.e., wavelet, at the same time, is proposed. Then the results are blended by multi-level perceptron (MLP) with two hidden layers, which generates the final type of beat. Authors consider and study 3 approaches of ECG classification on MIT-BIH arrhythmia database [14]. First, they provided study on 7 class labels, separating class N into 3 classes (to distinguish L and R from N class), then they employed four class labeling, namely, N (normal and bundle branch block beats), S (supraventricular ectopic beats), V (ventricular ectopic beats), and F (fusion of N and V beats). At the last approach the authors studied binary ECG classification in more detail, focusing on distinguish of ventricular ectopic beats (VEB) from non-VEBs and also supraventricular ectopic beats (SVEB) from non-SVEBs.

3 Data Description

In this study, the open-source MIT-BIH arrhythmia database [14] was used to train the LSTM recurrent neural networks model. The ECG signals correspond to the shape of the heartbeat for the normal case and for cases affected by various arrhythmias and myocardial infarction. This dataset uses labels to create five different beat categories in accordance with the Association for the Advancement of Medical Instruments (AAMI) EC57 standard [15]: N (normal and bundle branch block beats), S (supraventricular ectopic beats), V (ventricular ectopic beats), F (fusion of N and V beats) and Q (paced beat or unclassifiable beat). Each heartbeat was mapped by at least two cardiologists. Each ECG signals in the dataset contains 187 heartbeat measurements. At position 188 was the class label.

4 Descriptive analysis of cardiovascular health based on machine learning model

This paper proposes an architecture of system “Cardio+” for linguistic summarization of a cardiovascular health that includes an automatic ECG classification based on LSTM based recurrent neural networks. Since, when forming medical conclusions, in addition to the ECG, the cardiologist analyzes various other health indicators, the system includes a module for combining the results of ECG classification with an assessment of cardiovascular risk by SCORE-scale [33]. The proposed system architecture can serve as an experimental model of support tool for medical decision making. The architecture of the CVD risk analysis system is shown in Fig. 1

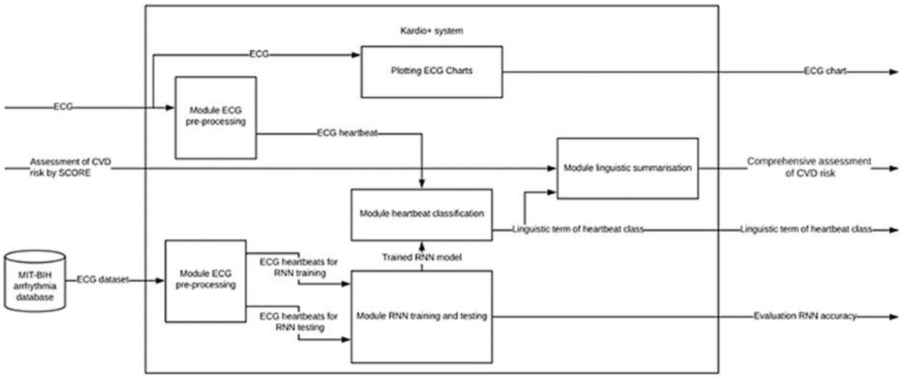

Fig. 1. The architecture of the proposed system for cardiovascular health analysis.

There are two main components in the system. The first component is designed for ECG classifier training and testing, the second one uses the trained model to classify new ECG and produces linguistic summarization of cardiovascular health taking into account the assessment of cardiovascular risk by SCORE-scale. Both components of the system “Cardio+” preprocess ECG signal to obtain heartbeat representation of equal length.

The input of the system receives data from the MIT-BIH arrhythmia database [14]. To solve the classification task RNN model using three LSTM layers and one MLP based layer is used.

The developed system makes it possible to analyze cardiovascular health based on the classification of heart rhythm pathologies in the ECG, integrating the heartbeat class obtained using the RNN model and the CVD risk indicator calculated using the assessment of CVD risk by SCORE-scale [33]. SCORE-scale assesses risk of fatal CVD within the next 10 years for patients in regions of Europe by gender, age, systolic blood pressure, total cholesterol and smoking. As a result of evaluating these indicators, an integer X is formed in the range from 0 to 47. The larger this number, the higher the risk of fatal cardiovascular events in a given patient. This paper examines four degrees of CVD risk according to the scale of assessment of CVD risk by SCORE [33]:

2=< X < 5: The 1st degree of risk (low risk) means that the probability of cardiovascular complications in this patient is less than 5%;

5 ≤ X < 10: The 2nd degree of risk (medium risk) assumes the probability of complications of 5-10%;

10 ≤ X ≤ 15: The 3rd degree of risk (high risk) implies the probability of complications of 10-15%;

X > 15: The 4th degree of risk (very high risk) implies a probability of complications of more than 15%.

Table 1 shows the developed rules that combine the heartbeat class recorded on the ECG and the degree of assessment of CVD risk by SCORE-scale. These rules made it possible to obtain a more informative comprehensive linguistic assessment of the risk of developing cardiovascular disease in a patient and formulate recommendations for a doctor.

The description of some details of the system implementation is given further.

Each ECG is read using the pandas library. The continuous ECG signal is split into windows using slices of arrays. A random number i from is selected and a slice of the array is taken from i to i + 3600. The amplitude values are normalized in the range from 0 to 1 using sklearn, which implements the normalization by the minimax criterion:

$$x_{i\_scaled} = \frac{x_i - \min(X)}{\max(X) - \min(X)} \tag{1}$$

Next, the set of local maxima X_{local_max} function of the signal module of the scipy library (see 28). From the set of local maxima, a set of R-waves() function of the signal module of the scipy library:

$$X_{local\_max} = \text{argrelextrema}(X_{scaled}) \tag{2}$$

From the set of local maxima, a set of R-waves X_R is found by applying a threshold value of 0.83. From a practical point of view, this is achieved by passing the appropriate condition to the where () function of the numpy library:

$$X_R = \text{where}(X_{local\_max} > 0.83) \tag{3}$$

Time intervals (I) are calculated as the difference between the indices of adjacent R-waves in the segmented ECG signal:

$$I_i = index(X_{R_{i+1}}) - index(X_{R_i}), i \in [0, 1, 2, \dots, len(X_R) \tag{4}$$

Table 1. Rules of linguistic assessment, combining the heartbeat class recorded on the ECG and the degree of risk, assessed by the SCORE scale

Degree by SCORE	ECG heart-beat classification mark	Information and advices to the doctor
1	N	Possible risk of developing CVD. There are no deviations in the work of the heart. Recommend a healthy lifestyle to the patient.
1	F, V	There is a risk of developing CVD. Abnormalities in the work of the heart according to ECG type F or V. Recommend a healthy lifestyle to the patient. Conduct additional research, prescribe treatment.
1	Q, S	There is a risk of developing CVD. Abnormalities in the work of the heart according to ECG type Q, S Recommend a healthy lifestyle to the patient. Conduct additional research, prescribe treatment.
2	N	Average CVD risk. There are no deviations in the work of the heart. Recommend a healthy lifestyle to the patient, monitor the SCORE scale indicators.
2	F, V	Average CVD risk. Abnormalities in the work of the heart according to ECG type F or V. Recommend a healthy lifestyle to the patient, monitor the SCORE scale indicators. Conduct additional research, prescribe treatment.
2	Q, S	Average CVD risk. Abnormalities in the work of the heart according to ECG type Q, S. Recommend a healthy lifestyle to the patient, monitor the SCORE scale indicators. Conduct additional research, prescribe treatment.
3	N	High risk of developing CVD. There are no deviations in the work of the heart. Recommend to the patient a healthy lifestyle, to carry out daily monitoring of the SCORE scale indicators and to perform electrography once a year.
3	F,V	High risk of developing CVD. Abnormalities in the work of the heart according to ECG type F or V. Recommend to the patient a healthy lifestyle, to carry out daily monitoring of the SCORE scale indicators and to perform electrography twice a year. Conduct additional research, prescribe treatment.
3	Q, S	High risk of developing CVD. Abnormalities in the work of the heart according to the ECG type Q, S. Recommend the patient to a healthy lifestyle, carry out daily monitoring of the SCORE scale indicators and perform electrography twice a year. Conduct additional research, prescribe treatment.
4	N	Very high risk of developing CVD. There are no deviations in the work of the heart. Recommend to the patient a healthy lifestyle, daily monitoring of SCORE scale indicators and electrography twice a year
4	F, V	Very high risk of developing CVD. Abnormalities in the work of the heart according to ECG type F or V. Recommend the patient to a healthy lifestyle, to carry out daily monitoring of the SCORE scale indicators and to perform electrography three times a year. Conduct additional research, prescribe treatment.
4	Q, S	Very high risk of developing CVD. Abnormalities in the work of the heart according to ECG type F or V. Recommend to carry out daily monitoring of the SCORE scale indicators and to perform electrography three times a year. Conduct additional research, prescribe treatment.

Then the period of the heartbeat of this segment is found. To do this, first the median value (m) of the time intervals between adjacent R-waves using the median () function of the numpy library takes. And for the period of the heartbeat (T), the value is taken equal to 1.2 * m:

$$T = 1.2 * median(I) \tag{5}$$

The maximum number of ECG time series points after the described changes is 187, but depending on T, there may be less of them. Since for the ANN needs to submit a standardized tensor to the input, the remaining part of the ECG time series, if it had less than 187 values, was supplemented with 0. The addition of exactly zero values was made due to the probability of accepting nonzero values for other types of teeth when training the classifier.

In this paper, data augmentation was performed using displacement and stretching of existing ECGs, as well as by adding a little noise.

Then the data goes to the Module ECG pre-processing. As a result of passing this module, a set of ECG time series is formed, which is later entered into the Google Colaboratory system record (ECG_classification_RNN.ipynb), where, based on the preprocessed data, a recurrent classifier based on LSTM neurons is trained and tested using machine learning tools. After training and testing, the best model (model.hdf5) is saved for later classification of the ECG signals. Now, for the analysis, it is enough to download the ECG signal (ECG_signal.csv). This signal enters the Module heartbeat classification, which uses pre-processing components, machine learning components, a Trained RNN model to classify and provide a linguistic assessment of the severity of CVD. Further, the data obtained during the analysis are sent to the Module linguistic summarization, which builds ECG and ECG time series graphs using the Matplotlib component.

A RNN based on LSTM neurons was implemented using Keras, a machine learning library that runs under the control of the Tensorflow library. It was decided to use the Tensorflow library, since it is an open development by Google and is included by default in the Google Colaboratory [34], in which the training of the created recurrent ANN was carried out.

The RNN contains four sequential layers: the first consists of 50 LSTM neurons, the second 25 LSTM neurons, the third contains 5 LSTM neurons, the last layer generates the network output and contains 5 multilayer perceptron, each with one hidden layer. For LSTM layers, it is obligatory to indicate the dimension of the structure supplied to the input - the input_shape () parameter, which is passed: the number of ECG for training (in our case, it is a little over 450,000); the number of points in the time series (n_features) (in our case, it is 187).

A parameter function is passed to all recurrent layers defining the activation function. In this work, the ReLU activation function was chosen, since recurrent networks with this activation function showed the best results in several applications. Softmax is used as the activation function for the last layer of the network, since it represents the output of the network as a probability distribution of belonging to each of the classes. After each recurrent layer, the probability of deactivation of each neuron is also set. Between the first and second, and the second and third layers, it is 0.2 for each neuron; between the third and fourth - 0.1 for each neuron.

The model of the network considered above was selected empirically. During the experiments, various structures of RNNs were considered: a different number of hidden layers (from 1 to 5); different types of memory cells (LSTM and GRU); different number of memory cells in each layer (ranging from 250 to 25 with a step of 25 neurons); different probability of deactivation of each neuron in the layer (probably varied from 0.3 to 0 with a step of 0.05). In this study, categorical cross entropy was chosen as the loss function, the adaptive method Adam was chosen as the gradient descent optimizer.

5 Classification Performance

Four main measures usually were considered in the literature to evaluate the performance of heartbeat classification models including the sensitivity (SEN), positive predictive value (PPV), accuracy (Acc) and F1-score:

$$SEN = TP/(TP + FN) \tag{6}$$

$$PPV = TP/(TP + FP) \tag{7}$$

$$Acc = (TP + TN)/(TN + FP + FP + FN) \tag{8}$$

$$F1=2*(PPV*SEN)/(PPV+SEN), \tag{9}$$

where TP (True Positive), TN (True Negative), FP (False Positive) and FN (False Negative) indicate the number of heartbeats correctly labeled, number of heartbeats correctly identified as not correspond to the heartbeats, number of heartbeats that incorrectly labeled, and number of heartbeats which were not identified as the heartbeats that they should have been, respectively.

Estimates of the accuracy of the ECG classifier, implemented on the basis of RNN for five classes of heartbeats (N (normal and bundle branch block beats), S (supraventricular ectopic beats), V (ventricular ectopic beats), F (fusion of N and V beats) and Q (paced beat or unclassifiable beat) are given in Table 2.

Table 2. Results of ECG classification

Class	**PPV**	**SEN**	**F1**
N	0.96	0.94	0.95
S	0.95	0.98	0.96
V	0.97	0.96	0.97
F	0.96	0.97	0.97
Q	1.00	0.99	0.99

The total number of ECG records on which the RNN based classifier was tested was 4000 samples, and 800 samples were selected for each of 5 classes for testing.

Table 3 compares the performance of proposed RNN classifier of ECG with classifiers from previous works. For comparison the classifiers from the works [13, 16, 19, 28] were chosen as they used the same MIT-BIH arrhythmia database [14]. Note that these studies used more complex models of classifiers, so in [13] 13-layer deep learning model based on CNN is used to classify ECG, in the study [28] authors combined three types of neuron networks: CNN, BiRNN sequence to sequence model and RNN with LSTMs to classify ECG.

In this contribution we utilize LSTM based RNN model which contains four layers. It should be noted that the authors in [28] classified only 4 classes of heartbeats, while in this work the ECG was classified into 5 classes.

Comparison of the classification results according to the criteria of average accuracy is shown in Table 3.

Table 3. Comparison machine learning for ECG classification

Authors	Approach	Accuracy
R. J. Martis *et al.* [19]	Feed-forward Neural Network	94.52%
U. R. Acharya *et al.* [16]	9-layer CNN	94.03%
M. Kachuee *et al.* [13]	13-layer CNN	93.4%
S. Mousavi *et al.* [28]	CNN, BiRNN with LSTM	99.92%
Proposed	RNN with LSTM	98.34%

According to Table 3, the average percentage of correct answers for the proposed RNN model for ECG classification is 98.34%, so the accuracy achieved in this work is competitive with modern models.

Unlike other studies a system of rules that integrates the heartbeats class and the patient's SCORE assessment was developed to provide a linguistic description of cardiovascular health, useful in forming a medical conclusion.

6 Conclusion

Operational analysis and automatic diagnosis of cardiovascular diseases is an important and urgent task in medical practice. The development and application of machine learning methods that allow solving this problem will improve the quality of medical services provided, identify diseases at an early stage and inform patients about the decline in cardiovascular health. In this work, a modular structure of a system for analysing cardiovascular health is proposed and implemented, in which, on the basis of the developed RNN model, an automatic classification of the patient's ECG is performed, the results of which are integrated with the degree of development risk to generate useful information for the doctor in a linguistic form. The developed LSTM based RNN has a simple architecture and, on the MIT-BIH arrhythmia database, has been shown to be effective in classifying ECGs into five classes. In this study, we obtained the highest average accuracy of 98.34%. In addition, a feature of this study is the possibility of integrating the assessment of CVD risk by SCORE with the results of ECG classification. Further research is planned towards the development of the Cardio+ system to expand the integration of CVD indicators characterizing the behavioral, anthropological and psychological characteristics of patients.

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References

1. Joonseok Kim, Peter W. Groeneveld: Big Data, Health Informatics, and the Future of Cardiovascular Medicine. Journal of the American College of Cardiology Feb 69 (7), 899- (2017).
2. Guo, Q. *et al*.: Cluster analysis: a new approach for identification of underlying risk factors for coronary artery disease in essential hypertensive patients. *Sci. Rep.* **7**, 43965; doi: 10.1038/srep43965 (2017).
3. Shylaja .S.: Classification of Data for Cardiovascular Disease Prediction System Using Multi-Layer Perceptron. Journal of Advanced Research in Dynamical and Control Systems 11(6), 850-856 (2019).
4. Umair Shafique : Data Mining in Healthcare for Heart Diseases. International Journal of Innovation and Applied Studies 10(4), 2028-9324 (2015).
5. Atrial Premature Beats, https://www.msdmanuals.com/home/heart-and-blood-vessel-disorders/abnormal-heart-rhythms/atrial-premature-beats, last accessed 2020/10/10.
6. Atrioventricular Block, https://www.msdmanuals.com/professional/cardiovascular-disorders/arrhythmias-and-conduction-disorders/atrioventricular-block?query=Atrial%20escape last accessed 2020/10/10.
7. Supraventricular premature beats, https://www.amboss.com/us/knowledge/Supraventricular_premature_beats last accessed 2020/10/10.
8. Premature ventricular contractions (PVCs), https://www.mayoclinic.org/diseases-conditions/premature-ventricular-contractions/symptoms-causes/syc-20376757, last accessed 2020/10/10.
9. Bokerya L.A., Goluchova E.Z.: Clinical cardiology: diagnostics and treatment, Moscow: publishing House of the Bakulev national research center (2011) (in rus).
10. Antonis A. Armoundas, Gordon F. Tomaselli and Hans D. Esperer: Pathophysiological basis and clinical application of T-wave alternans. Journal of the American College of Cardioogy 40,. 207-217 (2002).
11. Teijeiro T., Flix P., Presedo J. and Castro D.: Heartbeat classification using abstract features from the abductive interpretation of the ecg. IEEE Journal of Biomedical and Health Informatics 22 (2), 409–420 (2018).
12. P. de Chazal and Reilly R. B.: A patient-adapting heartbeat classifier using ecg morphology and heartbeat interval features. IEEE Transactions on Biomedical Engineering.. 53(12), 2535–2543 (2006).
13. Kachuee M., Fazeli S., Sarrafzadeh M.: ECG Heartbeat Classification: A Deep Transferable Representation ECG Heartbeat Classification, https://arxiv.org/pdf/1805.00794.pdf, last accessed 2020/10/10.
14. Physionet MIT-BIH arrhythmia database, https://www.physionet.org/physiobank/database/html/mitdbdir/tables.htm, last accessed 2020/10/10.
15. AAMI-recommended practice: Testing and reporting performance results of ventricular arrhythmia detection algorithms. Arlington, VA: Association for the Advancement of Medical Instrumentation (1987).
16. Acharya U. R., Oha Shu Lih, Hagiwara Yuki, Tan Jen Hong, Adam Muhammad, Gertych Arkadiusz, San Tan Ru. A Deep Convolutional Neural Network Model to Classify Heartbeats, https://www.researchgate.net/publication/319271551, last accessed 2020/10/10.

17. Pan J., Tompkins W.J.: A simple real-time QRS detection algorithm, https://www.researchgate.net/publication/3728672_A_simple_real-time_QRS_detection_algorithm, last accessed 2020/10/10.
18. Z-Score: Definition, Formula and Calculation, https://www.statisticshowto.com/probability-and-statistics/z-score, last accessed 2020/10/10.
19. Martis R. J., Acharya U. R., Lim C. M., Mandana K., Ray A. K. and Chakraborty C.: Application of higher order cumulant features for cardiac health diagnosis using ECG signals. International Journal of Neural Systems, 23(4), (2012).
20. Wavelet Transform, https://www.sciencedirect.com/topics/computer-science/wavelet-transforms, last accessed 2020/10/10.
21. Haykin S. S.: Neural networks: a comprehensive foundation, 2nd Edition, Prentice Hall, (1999).
22. Graves, A.: Supervised Sequence Labelling with Recurrent Neural Networks. Studies in Computational Intelligence. Springer. (2012).
23. Afanasieva, T., Platov P.: The Study of Recurrent Neuron Networks based on GRU and LSTM in Time Series. In: 6th International conference on Time Series and Forecasting, pp. 190-202, Granada (2019).
24. Junyoung Chung, Caglar Gulcehre, KyungHyun Cho, and Yoshua Bengio: Empirical evaluation of gated recurrent neural networks on sequence modeling, https://arxiv.org/pdf/1412.3555.pdf, last accessed 2020/10/10.
25. Laptev N., Yosinski J., Li Erran, and Smyl S.: Time-series extreme event forecasting with neural networks at uber. In International Conference on Machine Learning 34 (2017).
26. Hojjat Salehinejad, Sharan Sankar, Joseph Barfett, Errol Colak, and Shahrokh Valaee: Recent Advances in Recurrent Neural Networks, https://arxiv.org/pdf/1801.01078.pdf, last accessed 2020/10/10.
27. Zachary C. Lipton, John Berkowitz, Charles Elkan : A Critical Review of Recurrent Neural Networks for Sequence Learning, https://arxiv.org/abs/1506.00019, last accessed 2020/10/10.
28. Mousavi S., Afghah F., Acharya U.R.: Inter- and Intra-Patient ECG Heartbeat Classification For Arrhythmia Detection: A Sequence to Sequence Deep Learning Approach, https://arxiv.org/pdf/1812.07421.pdf, last accessed 2020/10/10.
29. Kyunghyun Cho, Bart van Merriënboer, Caglar Gulcehre, Dzmitry Bahdanau, Fethi Bougares, Holger Schwenk, Yoshua Bengio: Learning Phrase Representations using RNN Encoder–Decoder for Statistical Machine Translation, https://arxiv.org/pdf/1406.1078.pdf, last accessed 2020/10/10.
30. Hochreiter, S. and Schmidhuber, J.: Long short-term memory. Neural Computation, 9(8):1735–1780 (1997).
31. Schuster M., and Paliwal K.K. : Bidirectional recurrent neural networks. IEEE Transactions on Signal Processing 45(11), 2673–2681 (1997).
32. Saadatnejad S., Oveisi M., Hashemi M: LSTM-Based ECG Classification for Continuous Monitoring on Personal Wearable Devices. IEEE Journal of Biomedical and Health Informatics (JBHI) (2019). https://www.researchgate.net/publication/329608349_LSTM-Based_ECG_Classification_for_Continuous_Monitoring_on_Personal_Wearable_Devices, last accessed 2020/10/10.
33. SCORE, https://www.escardio.org/static_file/Escardio/Subspecialty/EACPR/Documents/score-charts.pdf, last accessed 2020/10/10.
34. Google Colaboratory, https://colab.research.google.com, last accessed 2020/10/10.