REVIEW

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Prospects for the use of neural networks in cardiometry

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Abstract

This paper provides an overview of the use of neural network technology in cardiology, primarily in diagnostics using ECG. The aim of this work is to substantiate the use of artificial neural network technology in cardiometry, as a field of science that is closely related to cardiology, but differs from it in the wider use of natural science approaches. The definition of machine learning is given, and the concept of artificial neural networks as one of the methods of machine learning is defined. The mechanism of electrocardiogram recording is described and methods of its analysis are considered. The types of neural networks used for electrocardiograms processing are revealed. The prospects of using the neural network method for processing the data obtained during cardiometric studies are determined.

Keywords

Artificial neural network, ECG, Cardiometry

Imprint

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Introduction

Research of the human biological field is one of the most important diagnostic techniques in modern medicine. The human biological field includes a variety of acoustic, thermal and electromagnetic radiation, the study of each of which allows you to identify the pathology of the functioning of the body as a whole, individual organs and organ systems. During the examination, doctors receive huge amounts of data, which takes a long time to process. Automation of this process is necessary to reduce the time required for analyzing the received data.

Artificial intelligence systems show some success in the analysis and classification of large data sets and allow us not only to automate the analysis processes, but also to perform it in order to identify certain patterns of changes in different characteristics.

The aim of the work is to review the application of artificial neural network (ANN) technology in classical cardiological research, primarily based on the use of ECG.

The research is relevant due to the trend of increasing use of neural networks in various fields. Research on the use of neural networks in medicine indicates a wide potential for the development of this area. Neural networks can improve the accuracy and speed of diagnostics, and, consequently, improve the quality of medical services.

The task of this study is to substantiate the feasibility of using ANN technology in cardiometric research. The novelty of the work consists in the fact that the ANN technology is used for the first time in cardiometry. Cardiometry, as a field of science, is closely related to cardiology, but differs from it in the wider application of natural science approaches. Accordingly, it is possible to use in cardiometry the experience of the ANN application accumulated in classical cardiology.

Concept of artificial neural networks

ANNs are designed taking into account the type of input and output data, the task set and the classified features, the principles of minimizing unnecessary memory consumption in the executing computer. [1,2]

Machine learning (ML) is a class of artificial intelligence methods that provide a solution to a problem by searching for an algorithm using a pre-selected array of use cases for solving similar problems.

The main methods of ML are neural networks. Artificial neural network algorithms can be effectively used to solve classification problems, such as in cardiograms. Neural networks are a set of algorithms of the A(X) type that take as input a number of parameters of studied object X, and output the Y answer.

The elementary unit of the NN is a neuron, that is an algorithm that takes the K-th number of elements i as input and outputs an expression of the following form:

$$o = a\left(\sum_{n=1}^{k}\left(i_n \cdot W_n\right) + W_b\right), \qquad (1)$$

where a is the neuron activation function;
W_n – weight coefficient of the corresponding input;
W_b – the coefficient of deviation.

Neuron activation function is a function that determines the dependence of the input signal on the normalized values of the interval [0; 1] or [-1; 1].

Weight coefficients characterize the significance of the corresponding input and are determined during the NN training process. The weighting factor is the main characteristic of the connection between neurons, called a synapse.

Functionality error is a function that determines the dependence of the weight coefficient value on the deviation of the output in the NN that used this value.

Figure 1 shows a scheme of work of the simplest feedforward neural network. This neural network is very likely to determine the gender of a particular person based on their weight and height, taking the values of weight and height indicators of millions of people of different genders as training.

A neural network is a composition of at least one input neuron, one output neuron, and one hidden neuron.

Neural networks are divided into feedforward and recursive. In feedforward NN, the signal propagates from the neurons of the n-th layer only to the neurons of the n+1 layer, so the input of one neuron of a certain layer can only be the outputs of the neurons of the previous layers. The signal in recursive NN can propagate along an arbitrarily complex path, which is why the input of any neuron in a recursive NN can be made up of the outputs of any of the neurons in the same NN.

The key feature of the ANN is the need to train it, i.e., to select the weight coefficients w, so that the model outputs the result that the developer requires from it. For this purpose, a data sample is used that contains a set of parameters X (for example, anamnesis, data from functional research methods, analysis results, images) and a known outcome Y (for example, hard or soft endpoints highlighted in the image of the area of interest). In this case, the weight coefficients are not defined in advance, the task of the ANN is to calculate them independently. [3]

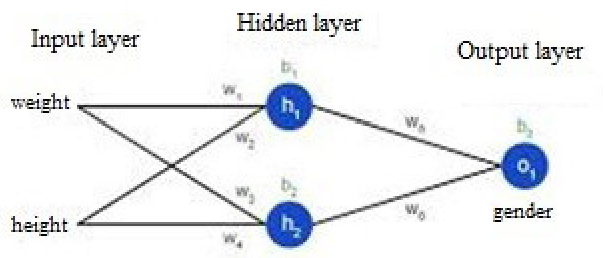

Fig.1. General scheme of the NN performance

An indisputable advantage of ANN over typical linear algorithms or statistical methods (for example, implemented in MS Excel [4], Statistica [5]) used when working with medical data is its ability to learn with data analysis, finding relationships and then presenting independent results [6, 7]. However, this approach also has a significant disadvantage: the requirement for a large sample of clinical cases with a known outcome. During development, you can not only change the ANN topology, but also the number of parameters included in its training [8]. The development of ANN has led to the study of data from the point of view of deep learning, i.e. identifying patterns in the available information [9]. Compared to packages for processing statistical data, for example, Statistica, ANN can detect unobvious relationships between the studied features and the relationship between input features and predictions

Application of neural networks in classic cardiology

Analysis of medical databases shows that diseases of the cardiovascular system occupy the second place in the number of studies conducted using ANN (Fig. 1). More than 30 thousand works on this topic have been published over the past 5 years. This indicates a high degree of applicability of ANN in cardiology. The possibilities of using artificial neural networks (ANN) in cardiology are reduced to three main application groups: decision support systems (DSS); forecasting, in particular, the outcomes of CVD treatment; risk assessment, including the risks of CVD development, based on a wide range of input data.

Analysis of the use of neural network technologies for the diagnosis of various diseases in the field of cardiology has shown that the most optimal model of artificial neural networks for solving problems of medical diagnostics and forecasting is a multi-layer

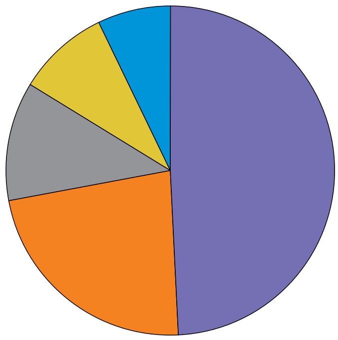

Fig.1. The number of studies on the use of ANN in five leading areas of healthcare over the past 5 years.

perceptron, which is a direct propagation network in which neurons of one layer are sequentially connected to neurons of adjacent layers without recurrent connections. It is also revealed that the most optimal algorithms for training a multi-layer perceptron are the error back propagation algorithm and the genetic algorithm. The high accuracy of neural network diagnostic models described in the literature indicates the prospects of using artificial neural networks in cardiology. The impementation of neural network diagnostic models into clinical practice can provide effective assistance in making medical decisions, improve the quality and accuracy of disease diagnostics, and reduce the time for patient examination.

For example, in 2017, A. Caliskan and M. Yuksel [10] published a scientific paper describing the possibility of using deep neural networks in the diagnosis of coronary heart disease. Diagnostics in that study was considered as the task of classifying patients into two groups: "patient is healthy" and"patient is sick". The network was trained in two stages. The patient's age and gender, as well as laboratory blood test and ECG parameters were used as training parameters. The neural network was trained on two sets of data: in the first case, the network classified patients with an accuracy of 87.6 %, in the second-with an accuracy of 89.7 %. L. N. Yasnitsky and co-authors [11] proposed a neural network model that allows identifying 9 diseases of the cardiovascular system based on 51 input parameters that characterize the patient and his symptoms. The same authors in their later research modified the previously developed neural network system, adding to it the ability to predict the course of diseases in different periods of their development. In addition, the number of input parameters was increased to 62, and the number of possible diagnoses was reduced to 6. As a practical significance of the developed neural network system, the authors point out the possibility of modeling various variants of the disease prediction for each patient under examination. There are also examples of the use of ANN for the analysis of pathological changes in blood vessels [12].

In the study [13], the authors used recurrent ANN for early detection of the onset of heart failure. This study used 3,884 cases of heart failure to train ANN and data from 28,903 people in the control group who are emergency care patients. Each of them had 72 clinical codes describing their condition. It is emphasized that ANN has shown excellent effectiveness in predicting the onset of heart failure compared to popular methods. Thus, using a 12-month observation window, the ANN showed an average accuracy of 75.2 %, and at 18-month – 85.9 %.

A team led by P.-F. Tsai [14] developed an ANN-based system for predicting the length of hospital stay for patients with one of the three main diagnoses: coronary atherosclerosis (CAS), heart failure (HF), and acute myocardial infarction (AMI). A total of 2,377 admitted patients with cardiac disorders were used. The training sample included data from 744 admitted patients with CAS and 1155 with HF and AMI. The test group consisted of data from 189 patients with CAS and 289 with HF and AMI. During training, 70 % of randomly selected data was used for training the ANN, and the rest was used for validation. The use of the ANN model allowed us to correctly predict the time of inpatient stay of patients with CAS 88.07 % - 89.95 % at the discharge stage and 88.31-91.53 % at the admission stage. For patients with AMI or HF, the accuracy ranges from 64.12 % to 66.78 % at the discharge stage and from 63.69 % to 67.47% at the admission stage, when an error of two days is allowed. Thus, using the proposed method, you can plan the work of a medical and preventive institution, its workload, i.e. solve administrative issues.

In the work of S. Nanayakkara and co-authors [15], in-hospital data available during the first 24 hours after patient admission were used to develop a more accurate risk prediction model using both logistic regression and machine learning methods, combined with demographic, physiological, and biochemical information. The input parameters for ANN were the following: age, gender, comorbidities and remission status at admission to the intensive care unit, individual components of the Glasgow coma scale before sedation, urine output, the highest and lowest physiological and biochemical parameters, as well as the need for artificial ventilation during the first 24 hours after admission to the intensive care unit and the number of hours in hospital before admission to the intensive care unit. In total, the study involved 48,485 patients admitted to intensive care units in Australia and New Zealand who were diagnosed with cardiac arrest outside the hospital. After exclusion, 39,566 patients included in the analysis were left, of which 45.6 % (18,019) did not live to be discharged from the hospital. The results obtained show that clinicians can use that ANN to predict a possible fatal outcome, since the accuracy of the algorithm was 97 %. [16]

Application of neural networks in electrocardiogram processing

Electrocardiogram and methods of its analysis

Heart has the property of automatism, independent generation of electrical impulses. Electrocardiography (ECG) is a method of analyzing the heart performance, based on the recording of electromagnetic field disturbances that occur in the heart muscle during the heart cycle. An electrocardiogram reflects the energy processes in the heart muscles that determine their contraction. An ECG contains information about the following:

1. Biochemical processes that determine the quality of heart muscle contraction.
2. Time points of the beginning of action pulse generation in the SA and AV nodes.
3. Cardiac cycle phases duration.
4. Heart muscles contraction amplitude.
5. Anatomic changes in the muscle-valve system.
6. Systemic processes that regulate the heart rate.

The signal that displays the nature of these disturbances is called an electrocardiosignal (ECS).

ECS analysis is the process of studying the ECG signal, aimed at detecting pathological deviations in its individual sections and determining the causes of these deviations.

The task of electrocardiosignal classification is to identify informative signs and find their dependence on the corresponding heart disease or its absence.

There are a large number of signs of heart failure, reflected on the ECG.

Neural networks are often used by researchers to solve problems of classification of the ECG. The reasons for this are the following advantages of neural networks:

Table 1.
Accuracy of using different types of NN in the study of a single ECG segment

ECG segments / Types of neural networks	Accuracy, %
RR-interval / multi-Layer PNN, FFNN, modular NN	86.67
RR-interval R-peak / Multi-Layer PNN	99.99
R, Q, S, P, T-peaks, RR, PR, QT, ST, QRS-intervals, ST segments / Straight PNN	96.5
R-peak, RR-interval / FFNN, back propagation method	95
QRS complex amplitude, RR interval / FFNN, combination of odd logic and multi-layer PNN	85
QRS-complex / MLPNN, RBFNN	99.55

- capability of establishing non-linear relationships between input and output signals that cannot be described by traditional methods;
- the same, and in some cases even higher, accuracy of the results obtained in comparison with statistical and deterministic methods;
- high resistance to noise and time deviations of the signal.

However, neural networks have a number of disadvantages, such as:
- probability of failure to reach the global minimum of the functionality error;
- non-requirement of building an optimal algorithm for all 12 ECG leads.

According to the study by Zahra Ebrahimi, out of 75 articles published in 2017-2018 on the use of NN in ECG processing, the following deep learning methods were most actively used: Convolutional Neural Network (CNN), Deep Belief Network (DBN), Recurrent Neural Network (RNN), Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU). CNN was used in 52% of the studies. These methods showed high accuracy in the classification of atrial fibrillation (100%), supraventricular ectopic contractions (99.8%), and ventricular extrasystoles (99.7%).[17]

First of all, I would like to pay attention to the convolutional type of neural networks, which are most often used for image analysis and classification. Such neural networks operate with forms that they are trained to distinguish. Practice shows that such networks can be used to analyze the graphical representation of an ECS. It should be noted that this method does not require prior identification of specific features and is invariant to schedule shifts.

Table 1 shows the results of researchers using different types of neural networks to classify the most informative ECG segments. The research was conducted from 2009 to 2014 by S.Jadhav, M. Vijayavanan, V. Srivastava, R. Ghongade and others.

The use of ANN in the field of ECG processing is considered from the point of view of applying wavelet transformations [18] with an average accuracy of 97.5%, 98.4%, and 97.2% for determining P-waves, QRS complexes, and T-waves, respectively. However, the use of ANN allows you to increase the speed and quality of analysis of such data. In the work of G. Sannino and G. De Pietro [19], a deep learning ANN was used for automatic classification of ECG signals. We used the MIT-BIH data set [20, 21], which contains 48 half-hour recordings from two-lead ECGs of 47 patients. The signal processing consisted of the following steps: noise reduction; determination of peaks on the ECG signal (identification of the P -, T-waves and R-peaks location); segmentation of the signal into single heartbeats, which will be assigned to the "healthy" and "pathological" group; extraction of additional information about the signal (splitting into heartbeats leads to loss of information about the profile of individual pulsation and signal variability). Each half-hour ECG segment was divided into five-minute segments, giving a total of 84,615 unique recordings. Their classification showed that 66750 records met the criteria of the "normal" group, 2288 "pathological" (containing premature ventricular contractions, supraventricular premature contractions or mergers of ventricular and normal contractions), and 14828 were unclassifiable and then excluded from consideration. As a result of this data preparation, 2288 records from the "healthy" group were randomly selected for further work. In total, 60% of 4576 records were selected for the training set (1466 records from the "healthy" group and 1246 from the "pathological"group). The developed deep learning ANN was created using Google TensorFlow (Google, USA) and showed extremely high accuracy (more than 99%), compared to other algorithms.

Prospects for using artificial neural network technology in cardiometry

Fig. 2 shows a diagram of interaction between a doctor and a patient in the framework of a recommender system based on the ANN. A set of ECGs recorded with cardiometric method will be a training sample. The ANN processes ECGs of patients. ECGs are divided into the following segments: RR-interval R-peak, S, P, T-peaks, PR, QT, ST, and QRS-complex. Each segment is processed by a specific type of the

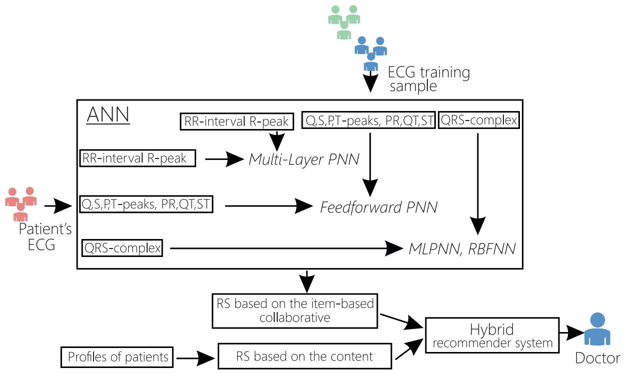

Fig.2. Scheme of interaction between doctor and recommender system based on ANN.

ANN: Multi-Layer PNN, Feedforward PNN, MLPNN, RBFNN. The type of the NN is determined on the basis of already conducted studies that have established the highest accuracy of this particular type in relation to this particular segment [15]. The received data is then passed to the recommender system based on the item-based collaborative filtering. In parallel, patient data is entered in the profile and processed by the recommender system based on the content filtering. The aggregated data is passed to the hybrid recommender system segment, which, in turn, passes the final result to the doctor for review.

Conclusion

The advantages of ANNs over medical information systems and statistical methods are the ability to train on large sets of parameters with unknown patterns between input and output data. ANNs make it possible to obtain more accurate descriptions of the studied parameters, as well as to display the dynamics of statistical properties of various indicators. Modeling of real situations for solving problems is carried out by analyzing knowledge from their own experience, acquired by the ANN independently. The results of the ANN performance are subject to minimal impact on the final result of the clinician's subjective factor and experience (positive or negative), or are completely separated from them. The use of ANN allows you to manually edit the values of individual parameters and their properties, as well as other ways to include expert knowledge in the network. The use of ANNs also provides a flexible tool for situations where immediate decision-making is required.

The use of ANNs in medicine is a promising direction, since their development will increase the amount of the processed data. Implementation of the ANN will allow the following:

* make it easier and faster to work with patients;
* improve the quality of medical services provided by selecting a personalized treatment method;
* predict the course of disease;
* detect diseases at an early stage;
* use telemedicine for remote settlements where modern medical care tools are not available.

From an economic point of view, the use of ANN can reduce the amount of time spent on data processing and diagnostics, which theoretically can reduce the workload of clinicians. This will allow you to devote more time to complex cases, which have a positive impact on the quality of medical care and reduce adverse outcomes in cases of serious diseases.

All of the above advantages of NN can be successfully applied in cardiometry. The use of NN in cardiometry will undoubtedly improve the quality of diagnostics and the efficiency of its implementation, and also opens up wide opportunities for improving the quality of health care in general, by screening wide number of population. The data obtained by cardiometric ECG analysis are more accurate and easier to process by the ANN as compared to classical ECG data [23]. It is also possible to introduce an ANN-based segment as part of a broader medical recommender system [24, 25].

In the course of further research, it is planned to use the available results of numerous cardiometric ECGs of patients of different gender, age and health status to build an ANN based on their data. The ANN's segment is supposed to be a part of the recommender system.

Statement on ethical issues

Research involving people and/or animals is in full compliance with current national and international ethical standards.

Conflict of interest

None declared.

Author contributions

The authors read the ICMJE criteria for authorship and approved the final manuscript.

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