

Using The Machine Learning Method in Portable ECG Monitoring System to Identify Diagnostically Complex Heart Diseases

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Abstract—Due to the high level of disability and death caused by heart diseases worldwide, the problem of combating cardiovascular diseases is becoming more and more important and relevant. In fact, one of the leading causes of death worldwide has long been cardiovascular disease, according to the World Health Organization. Among heart diseases, the most dangerous to life is myocardial infarction. In connection with the rapid morbidity, early diagnosis of this disease is one of the topical problems of modern public health care. At present, although there is a wide range of different statistical, math methods and computer tools for the processing of cardiological information, the task of increasing the accuracy of methods for the analysis of electrocardiograms and diagnostic tools in this field of study remained relevant. Taking into account the imperfect tools and systems for diagnosing heart diseases, as well as the human factor, the lack of a method that can help doctors to diagnose myocardial infarction early requires the development of new diagnostic information methods. This article presents a neural network analysis methodology for diagnosing myocardial infarction based on the joint analysis of direct and reverse signs of myocardial infarction from electrocardiographic information obtained from a portable cardiac analyzer.

Keywords—*electrocardiography, portable ECG monitoring, electrocardiosignal, heart attack, infarct, neural network, machine learning, ECG device*

I. INTRODUCTION

Currently, there are portable devices for monitoring the state of the heart. For example, there are devices such as Holter, GE MAC5500, GE SEER Digital Holter, Philips Digitrack, BIOPAC MP150, ePatch from ePatch DELTA and Midmark IQmark. But the disadvantage of one device is that the patient is lying in bed or the device must be placed on the body for several hours. Based on the data obtained, the doctor analyzes the data offline. This method involves the direct participation of a doctor who does not perform work in real time. In addition, wearable devices such as smartwatches, Nuvant Corventis PiiX, AliveCor, SmartCardia INYU, and

MyThrob System on Chip (SoC) exist, but further Advancements in processing complexity, RAM, and autonomy time are yet to be made. According to research work by Chinese scientists over the past year, "Smart Clothing" has a portable device for determining the state of the heart [1]. The ECG signals from the filter are fed into the nRF52840 via the chip's AIN. The chip receives ECG signals and then transmits the signals to a smartphone via Bluetooth. However, it was found that the device could not detect any disease, although it could provide accurate information for patients with chronic heart disease and heart condition during exercise, and for high-level users of ECG signals [2]. The small device is intended to collect good resolution high quality ECG readings of the human body. New deep learning based cloud service developed for automatic and accurate detection of cardiovascular diseases. But a few limitations cannot continuously collect data, and the deep learning model has a vague mechanism [3]. The device mainly has an AD8233 AFE chip for measuring the biopotential signal for three noncontact electrodes and generating an ECG signal, and a CC2650 microcontroller for transmitting information for reading, filtering them [4]. It is powered by a 2000 mAh Li-ion battery. In addition, the device is intended for daily use, and not for diagnostic use. But the device is able to control QRS waves and to some extent P and T waves relatively accurately. The visibility of R and T waves will developed by an appropriate filter and further improvement in hardware in next nearest years [5]. The study described the new design of the device and the "invisible" ECG system. The form of a toilet seat makes it clear and provides ECG data. In the future, the work will be aimed at studying interject materials with potential resources and expanding the investigational component to evaluate treatment recipients with known pathological diseases. A renewed approach to public health systems. Through cloud processing of cardiac information, ECG diagnostic information can be obtained in a timely manner. The usage of portable electronic devices such as phones in the

process of observing the electrocardiographic parameters of the heart helps to elevation of the effectiveness of the diagnosis of electrocardiographic information. Apple Watch (Apple Inc. Cupertino, California, USA), Fitbit Sense (Fitbit Inc., San Francisco, California, United States) or Withings ScanWatch (Withings, Issy-les-Moulineaux, France) devices are capable of recording an ECG at the same time using metals, and an electrode on the front of the watch is located with a screen recording and can be controlled by a sensor, while the electrode in the second version is worn on the wrist and the screen is placed on the back panel [6]. These devices can better diagnose ECG arrhythmias, but additional ECG settings are needed to diagnose other difficult heart illnesses, such as myocardial infarction or ischemia. In recent years, the Holter Wireless Body network device (WBAN) has been developed. The Holter may be worn by the patient to record the ECG over a longer period of time [7]. In addition, this recorded data is diagnosed when the doctor examines the patient, although it becomes ineffective due to the fact that it takes a very long process. A small contactless ECG device is similar to the size of a credit card but, integrates electrodes, reception, processing and signaling circuits and allows you to easily wear and transfer information compared to stationary ECG monitoring devices. ECG devices provide a well-defined clear signal accuracy, and the final product makes a basic and simple solution for daily ECG monitoring [8]. In this study, mcardia free-living arrhythmia screening aims to test the convenience of outpatient ECG collection[9]. mCardia came in handy during the experience among users. The results showed the convenience, usefulness and good clinical use of Cardia. On the other hand, it can improve the patient's relationship between the symptoms of the disease and the symptoms associated with the normal state of the heart. The use of the electrode shirt is time consuming and causes discomfort to patients. In addition, the measurement of cardiac potential often produces incorrect signals due to improper attachment of the electrodes to the body surface due to various factors[10].

Today, devices and systems that detect a dangerous heart condition in real time and prevent death are still in need of improvement. According to a recent literature review of portable systems, it has become clear that the device is needed to diagnose complex cardiac diseases such as myocardial infarction. Our goal is to extend the capabilities of a handheld tool to monitor the heart using neural network techniques. The relevance of the article lies in the development of a method of neural network analysis of electrocardiac signal (ECS) to improve the accuracy of myocardial infarction diagnosis and determine myocardial localization.

Currently, the possibilities of application of machine learning methods for detection of complex diseases using a portable ECG machine developed at Satbayev University are being studied.

II. METHOD OF NEURAL NETWORK ANALYSIS OF ELECTROCARDIOGRAPHIC INFORMATION TO DETECT MYOCARDIAL INFARCTION

It is known that in order to improve the reliability of cardiac diagnostic methods, it is necessary to expand the capabilities of neural network analysis of cardiac signals. Determination of myocardial infarction, as well as myocardial location and type, is performed by analysis of ECS cardiocycle segments according to generally accepted

signs. Registration of electrocardiac signal (ECS) is carried out with strict observance of certain rules. We will determine the degree of damage to the heart muscle by examining the electrocardiac signals. Instead of being tied to official diagnoses, it is necessary to increase the possibilities of diagnosing myocardial infarction according to the signal received from certain recorders. Considering the above, we developed the structure of the NNA ECS method for diagnosis, shown in Fig.1.

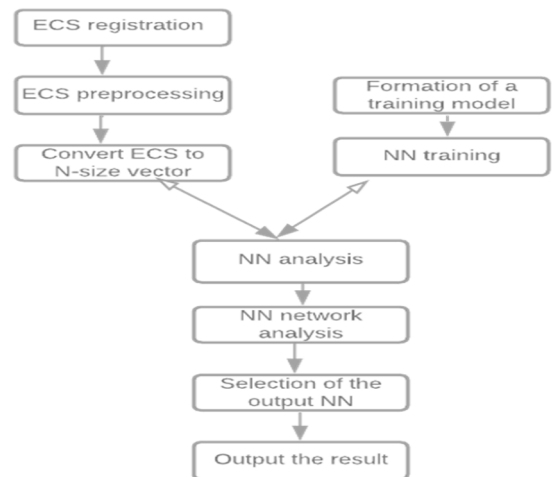


Fig. 1. Recommended approach to neural network analysis of ECS for myocardial infarction diagnosis

The main steps of the proposed approach to the NNA ECS, shown in Fig.1.

The registration of the ECS is performed using a portable ECG device, which: implements the function of extracting the ECS from the patient's body from 4 standard recorders [11-12].

In addition, wired (COM, LPT, USB, Ethernet, etc.) and wireless (InfraRed, Bluetooth, WiFi, etc.) communication channels can be used for data transmission. Computers of an arbitrary type (personal computer, laptop, NetBook, pocket computer, etc.) can act as a data processing device. At this stage, the withdrawal and registration of the ECS is carried out using the ECS registration device.

When registering an ECS, the following issues are resolved:

- at the location of the electrodes there are interaction between the electrode and the skin;
- electrical safety of patient;
- analog filter and ex magnification;
- ECS's selection and digitization;
- Pairing the ECS registration device with the computer.

After the registration period, the digitized ECS enters the computer's input.

Pre-processing of the ECS. This is where problems are addressed:

- digital filtering consisting of noise reduction and artifact elimination. Digital filtering is used to remove irregular beats from the recorded ECS;

- to distinguish characteristic features of the ECS: P amplitudes followed by Q, R, S, T waves and worth of midpoints among P and Q waves, S and T waves;
- the coefficient values can be obtained after implementing wavelet transform a Fourier and/or.

By the time finishing the preprocessing stage, we gain data information demonstrating the features of the collected ECS necessary to form an n-dimensional vector.

Representation of the ECS as an n-dimensional vector. N-dimensional vector can shaped from the achieved values in this stage. As a result, there will be two different alternatives of n-dimensional vector. The followed first case implements the features of the ECS that are the amplitudes (P, Q, R, S, T) of waves and values of the midpoints among them (P and Q waves, S and T waves). Therefore, second case shows that our n-dimensional vector are the coefficient values, which comes from the performance of the Fourier and/or wavelet, transform.

The formation of the training sample simply founded on the formation for each k heart condition of "its" ECS database for each lead involved and includes:

1. The analysis of the registered ECS within the skilled cardiologist and assignment of the registered ECS to one of k cardiac conditions according to the results of the analysis.

2. Statistical processing of formed for each of k cardiac conditions "its" ECS database. In order to make it:

- the ECSs number of one heart condition must be minimum of 50;
- the followed condition is splitted into 2 equal samples;
- the zero hypothesis that the samples under consideration belong to the same general population is made;
- t-test parameters are calculated
- - If $t_{\text{fact}} > t_{\text{table}}$, the correlation coefficient is considered meaningful and the zero hypothesis that the samples under consideration belong to the same general population is accepted.

3) Dividing the number of ECS of one heart condition into parts: training and control in the ratio of 4:1.

4) Dividing the training part of the number of ECS of one heart condition into two components (no-noise and no-noise) in the ratio 3:1.

5) Noisy ECS.

6) Using the obtained ECS (unnoised and noisy) to train k neural networks.

7). Using control ECS to test the training of k neural networks.

Training of neural networks. In the process action $k \cdot L$ (L is the number of leads) networks are learned and which a "its" ECS database, revealed in the result of the performed action before, is used.

As demonstrated by authors, LVQ adaptation NN structure parameters for ECS analysis consists in changing such NN parameters as:

- the dimensionality of the input vector;
- the amount of neurons in the competing layer;
- the amount of inner layers.

The paradigm of NN analysis contains discreteness of ECS, extraction of ECS signs of MI, processing them in NS, and evaluation of cardiac condition.

Every one of the 4 ECS signals in the outputs, a "different" LVQ network is used. The first analog electrocardiac (i.e., the ECS signal in each of the 4 leads) digitized according to SCP-ECG standard for digital ECS exchange and presented as 500 counts per cardiac cycle. Allocation of one cardiocycle is a distinctive feature: one cardiocycle is sufficient to detect myocardial infarction.

The values of samples of one cardiocycle of the ECS are fed to the inputs of the LVQ NN as an input vector x^h (shown Fig.2).

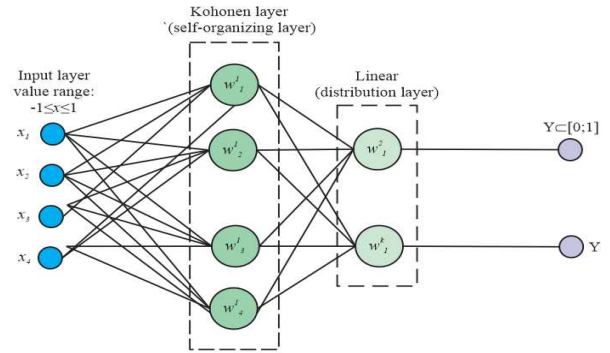


Fig. 2. NNA LVQ scheme for MI diagnostics.

The dimensionality of the input N_{in} vector is defined by the SCP-ECG standard for the replacement of digital ECS and is equal to $N_{in} = \{1 \div 500\}$.

The developed method ECS neural network analysis (NNA) allows to diagnose MI using LVQ neural networks. The value of the signal at the output of the LVQ NNA scheme used to diagnose the MI shown in Figure 2 is given by the following formula:

$$Y_k = F_{lin} \left(\sum_{j=1}^S w_{jk}^2 \cdot F_{compet} \left(\sqrt{\sum_{i=1}^N (x_i - w_{im}^1)^2} \right) \right) \quad (1)$$

where x_i is the i element of the input vector;

- w_{im}^1 – element i of the weights vector of the m -neuron of the competitive layer;
- w_{jk}^2 – element j of the weights vector of the k of the linear layer;
- F_{compet} – the transfer assignment of the competitive layer that determines the winning neuron;
- F_{lin} – linear instigation assignment of neurons of the dissemination layer;
- N – The size of the input vector NN;
- S – is the number of neurons in the competing layer;
- Y_k – The k -th output value of NN.

In analyzing the input data, the overall Euclidean dimension should be reduced to a minimum:

$$D = \sum_h \sum_i (x_i^h - w_i^{c(h)}) = \sum_h [(x^h, x^h) - 2(x^h, w^{h(h)} + w^{c(h)}, w^{c(h)})] \quad (2)$$

where h is the symbol of the input line, $c(h)$ class of disease appropriate to the line x^h .

By analyzing of expression (2), we can see that the problem of finding the minimum of D is identical to the problem of locating the expression's maximum:

$$\min D \rightarrow \sum_h \sum_i (x_i^h w_i^{c(h)}) \quad (3)$$

Number of neurons N_{coh} in the Kohonen layer represents the amount of clusters into which the input data is assumed to be split. The following formula is used to determine this value:

$$N_{coh} = \alpha \cdot N_{coh} \quad (4)$$

where α is the number of clusters per disease class.

After the parameters are determined, the LVQ NN is trained for every presenter. The aim of NS instruction in the ECS analysis is such an arrangement of neurons (choice of their weights) that it minimizes the magnitude of the amount of the anticipated distortion estimated by the reproximation error of the input $w_{x(h)}$ vector, by values of load of neuron-where p is the quantity of entry vectors.

$$E_q = \frac{1}{p} \sum_{h=1}^p \|x^h - w_{x(h)}\|^2. \quad (5)$$

where p is the amount of the input vectors

$w_{x(h)}$ - vector of poundage of the winning neuron when presented with the vector x^h

The completion criterion of the learning process NN is the execution of the necessary condition $E_q < \varepsilon$, where ε - the value of the error, set by the user before starting the training (for example, $\varepsilon = 0,01$).

The "convex combination" method is used to learn the LVQ NN for ECS analysis. The learning algorithm for LVQ NN works as follows:

- The same initial value is attached to all the Kohonen layer weights

$$w_i^m = \frac{1}{\sqrt{N_{in}}} \quad (6)$$

- Then the next vector is selectable from the learning sample x^h .
- The component of vector x^h . change in accordance with the formula

$$x = \beta(t) \cdot x^h + \frac{1 - \beta(t)}{\sqrt{N_{in}}} \quad (7)$$

where t is the symbol of the training epoch,

$\beta(t)$ - Is a monotonically growing functional, going from 0 to 1 as learning progresses.

4. For the Euclidean spacing distance of vector x' and of every neuron of the rivaling layer, see the following formula

$$d_m = \sqrt{\sum_{i=1}^n (x_i' - w_{im}^1)^2} \quad (8)$$

Where x_i is the value of the i element of the vector x' ,

w_{im}^1 - is the value of the i load of the m of the competitive layer's neurons.

5. The 2 The neurons with the shortest Euclidean space d_m to the enter vector x' are defined.

6. If condition is satisfied, the transition to step 7 is performed, otherwise it returns to step 2.

$$\min \left(\frac{d_1}{d_2}, \frac{d_2}{d_1} \right) > (1 - \varepsilon) / (1 + \varepsilon) \quad (9)$$

where d_1 is Euclidean spacing of vector x' and scales of the first discovered neuron,

d_2 is the Euclidean spacing of x' vector and the scales of the other neuron found,

ε - value selected from the range $0.2 \div 0.3$

7. The recovered neurons' weights are changed. If the classificatory classification of vector x' is correct, the correction is made by the above formula

In case of false classification, "rejection" is performed by formula

$$\omega_t = \omega_{t-1} + \eta_t (x - \omega_{t-1}) \quad (10)$$

$$\omega_t = \omega_{t-1} - \eta_t (x + \omega_{t-1})$$

where η_t is the value of the NN studying rate.

8. If learning error E_q is minimized, the learning cycle is terminated, alternatively, the process proceeds to step two.

NN analysis is performed simultaneously by parallel analysis of the registered ECS by each neural network. The output vector of every NN presents a single coded value, one - positive network response about affiliation to the k -state consistent with the disease, 0 - belonging to the healthy class. Subsequently, the analysis results in an array of data from outputs of neural networks.

Analysis of neural network leads. Data from outputs of NN goes to the logic blocks, designed to detect the corresponding heart state according to the decisive rules, and then to the priority encoder, designed to select the corresponding heart state. At the output of the priority encoder, the code of the input line number is formed, which receives a positive input signal from the output of one of k logical blocks of NN implicated in the analysis of ECS.

Output of the result. The number obtained by analysis of NN outputs is allocated a verbal characterization of the provided diagnostic inference about the heart condition of particular patient that is imformed to the customer.

There are structural scheme that implements the decision-making algorithm when making a diagnosis using the NNA ECS method is shown in Figure 3.

Since the main element of the structural scheme of the reliability of the functioning of the ECS NNA is the elements of the cardiocyclic NNA, from the point of view of reliability theory, it is obvious that the use of NNA in combination with various symptoms of myocardial infarction increases the likelihood of the disease in the patient.

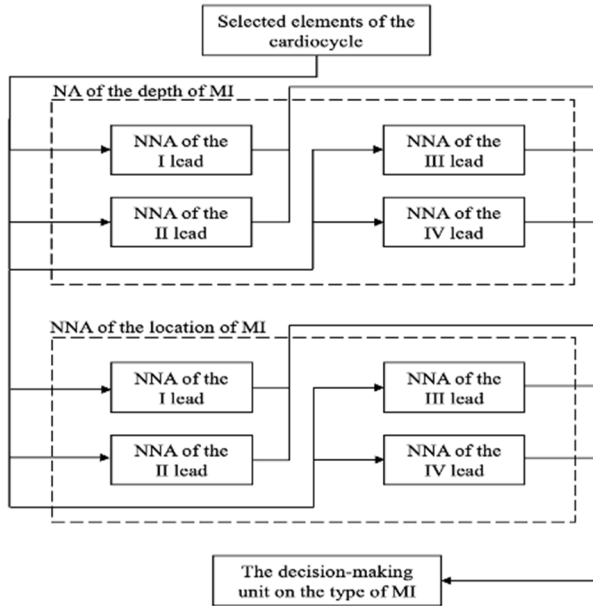


Fig. 3. Structural scheme of the approach proposed by NNA ECS.

The probability of a fault-free State of a device consisting of N parallel connected elements is determined by the theorem of adding the probability of joint random events:

$$P = (p_1 + p_2 + \dots + p_n) - (p_1 p_2 + p_1 p_3 + \dots) - (p_1 p_2 p_3 + \dots) - \dots - (p_1 p_2 p_3 \dots p_n) \quad (11)$$

It is known from the theory of reliability that the concomitant usage of different symptoms of myocardial infarction of NNA rise the likelihood of detecting the presence of the disease in a sick person. According to the rule of multiplying the probabilities of independent (aggregate) events, the authority of a product consisting of n elements is calculated with the formula:

$$P = 1 - \prod_{i=1}^n (1 - p_i) \quad (12)$$

that is, when independent (by reliability) elements are connected in parallel, their unreliability $(1 - p_i = q_i)$ is multiplied.

In the specific case where all elements have the same reliability, the formula is transformed as follows:

$$P = 1 - (1 - p)^n \quad (13)$$

In our case, the probability of correct diagnosis (sensitivity) for each neural network has its own value. Thus, the probability of determining the correct diagnosis in the case of combined use of NNA elements of the cardiocycle will be: $P = 0.997$.

The proposed NNA ECS method uses 28 LVQ. To analyze the localization of each of the 4 registers, 6 NN are performed (pathological Q -Wave, pathological R -Wave, ST -segment elevation, negative T -Wave, ST -segment depression, acute T -Wave) and 4 LVQs to analyze their depth, that is, one neural network for each register to analyze the absence of R -wave in the QRS complex.

We can improve a portable device developed at Satbayev University in a study so that it can predict heart disease in the future. As a result, by detecting complex heart disease, we can avoid dangers in a person's life.

III. CONCLUSION

An approach to the improvement of the NNA ECS method for diagnostics of cardiac diseases is proposed, which includes the following main stages: Signal registration, ECS pre-processing, neural network analysis of ECS, conversion of ECS into n -volume vector, formation of training models, training of neural network, analysis of NN, analysis of output making decision on presence of MI.

Electrocardiac neural network analysis was performed for brain diagnostics. The approach of ECS NNA has been proposed, the distinctive feature of which is the use of serial-parallel connection of MI when forming a training complex for the analysis of cardiocyclic segments. At the same time, along with determining the localization, the analysis of transmural or "depth" of the brain (absence of R -wave in the QRS complex) is performed.

ACKNOWLEDGMENT

The investigation has been funded by the Science Committee of the Science and High education Ministry of the Republic of Kazakhstan Grant «AP14969403- Study of methods machine learning algorithms for predict myocardial infarction».

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