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Siamese Neural Network's Models for Cardiac Arrhythmia Classification in the Conditions of Shortage of Training ECG Signals

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Abstract*—The article is focused on the development of Siamese neural network models for ECG signals classification that reflect cardiovascular pathologies, including arrhythmias, in the context of a limited amount of training data. The problem of a shortage of training data in machine learning for diagnosing heart disease is associated with a wide variety of pathological states and insufficient information for certain classes in open medical databases. The study aims to develop a complex method based on the combination of high-resolution electrocardiography and vectorcardiography with Siamese neural network architectures and training methods, which makes it possible to improve the accuracy of cardiac arrhythmias classification. The peculiarity of the proposed method, which is based on the ability of Siamese NNs to compare, is to detect and analyse the differences between the ECG signal under study and the generated reference feature vector of signals with pathology, which allows to effectively identify signal changes even for those diseases that are limitedly represented in the training dataset. In addition, to improve the efficiency of training, a method for generating a reference feature vector for pathological signals was developed. This vector is used by the Siamese neural network for comparison. The application of the principal component analysis (PCA) method allowed to extract key features from 100 ECG signals with pathologies, which contributed to the creation of a reference feature vector with a minimum number of training samples. Additionally, for each input ECG signal and reference feature vector, an average cardiac cycle was calculated, which helped to identify low-amplitude ECG components and features of the QRS complex. To implement the developed complex method, the PTB-XL database was used, which contains 12-channel ECG records classified into 70 disease categories. To reduce the impact of data imbalance, augmentation methods, as well as preprocessing methods were used to remove noisy signals and selectively reduce overrepresented classes. Two models of Siamese neural networks (NN) were developed as part of the study. The first model is focused on detecting low-amplitude pathological components of ECG signals, in particular, late atrial and ventricular potentials. The second model is designed to classify 18 types of arrhythmias and 19 associated pathologies, such as coronary heart disease, hypertrophy, and myocardial infarction. The effectiveness of the proposed NN specialised ECGnet network models was evaluated by comparing them with the specialised ECGnet network in the task of recognising late atrial and ventricular potentials. The first model exceeded the accuracy of ECGnet by an average of 10% and reduced the probability of false negative predictions. The second NN model for multi-class classification, which covered 37 diagnostic classes with rare diseases with less than 200 observations, exceeded the average accuracy of ECGnet by 10%, reaching a maximum increase of 28%. The obtained results allow to outline further ways to improve the complex method. In particular, improving the accuracy of ECG signal classification with pathologies is possible by using additional transformations of input features and methods of amplifying low-amplitude signal components.

Keywords — electrocardiography; Siamese neural networks; late ventricular potentials; late atrial potentials; cardiac arrhythmia; vector cardiography; singular value decomposition.

I. Introduction

Nowadays, various types of neural networks (NN) are actively used in automated diagnostic systems [1]. Usually, automated systems can make decisions and perform diagnostics using much less input data than is necessary for a doctor. This aspect of neural networks exists because of their high ability to identify hidden features and patterns, but it can cause false results due to overfitting [2]. To avoid such cases, it is necessary to use datasets with a large number of observations that could fully describe the variance of real diagnostic cases. Consequently, such systems are most often trained to detect common subgroups of diseases, for example, coronary heart disease, arrhythmia [3]. A more specific diagnosis may not be accurate enough due to the growing diversity between groups when analysing ECGs. As a result, more training data needs to be used to improve accuracy.

Analysed ECG signals may have different degrees of pre-processing, different sampling rates, number of leads, and high levels of noise. Due to the large number

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of cardiac diseases that can be simultaneously manifested in a single ECG record, the interpretation of such signals and diagnosis becomes complicated [4]. Unfortunately, due to the large variety of cardiovascular pathologies and their combinations, it is currently difficult to create training samples with the required amount of data. To solve this problem, approaches are being developed to improve training efficiency with a limited amount of training data [5], [6].

In addition to analysis of the classical ECG signal components with an amplitude range of 0.1 - 1 mV and frequencies in the range of 0. 5 - 40 Hz, to detect life-threatening tachyarrhythmias at early stages, low-amplitude ECG signal components can be analysed, namely, ventricular late potentials (VLP) and atrial late potentials (ALP) with amplitudes of 1 - 40 μV and frequencies of 40 - 250 Hz. Such components are usually detected by high-resolution electrocardiography (HR ECG) [7].

Another promising application of automated NN systems is digital medicine, where patients can receive basic diagnostics at home without wasting time in hospital queues and significantly reducing the healthcare cost [8]. The introduction of such systems would help to predict life-threatening conditions of the cardiovascular system and allow for timely medical treatment.

To improve the quality of biomedical signal classification, Convolutional layers are used in the architecture of neural networks. These layers analyse the morphological features of signals, which allows to analyse them at different levels of detalisation [9]. In addition, recurrent layers are used to analyse sequences, especially long-term signals. The use of these layers allows to extract time-dependent features from signals and, as a result, reduce the required amount of data for high-quality training [10].

For specific diagnostics tasks, combinations of different layers are used to create universal architectures. The ResNet neural network architecture is focused on detecting complex patterns in signals [11]. There are also specialised architectures for recognising certain types of data. The ECGNet architecture has special architectural solutions for detecting features in the ECG using various Convolutional layers and built-in attention mechanisms aimed at different signal components [12].

Siamese neural network architectures perform well when there is a lack of training data. These architectures efficiently identify differences in similar signals, and significantly reduce the amount of input data required to train a model. Siamese neural networks are used in personal identification tasks based on biomedical signals, such as ECG [13].

The study proposes a complex method for automated classification of ECG signals based on Siamese neural networks, which allows to effectively detect cardiovascular pathologies, in particular arrhythmias, with a limited amount of training data. The main peculiarity of the complex method is a combination of high-resolution electrocardiography and vector cardiography methods for preprocessing ECG signals, as well as application Siamese neural network architectures of cardiac arrhythmia classification by detecting and analysing structural differences between the signal under study and the reference feature vector of signals with pathology. In the study, the input data dimensionality was reduced by transforming from the 12-lead system to the orthogonal Frank system of ECG, which allowed to get more compact but informative signal representations. In addition, a special format of input data was used, which is presented in the form of averaged cardiac cycles and generalised feature vectors extracted by PCA, which ensures efficient detection of key features of ECG signals while keeping the low dimensionality of the input data. In the Siamese neural network architectures of the proposed method, two-layer Convolutional subnets are used to facilitate a more accurate comparison of signals by analysing the cardiac cycle shape and ECG signal structure simultaneously.

II. Materials and Methods

A. Classical Siamese neural network construction basics

The Siamese neural network of the classical architecture (Fig. 1) consists of two identical subnetworks with the same weights that are updated synchronously during training. This feature requires the same dimensionality of the data that are received at the input of each subnetwork. The main function of the hidden layers of this network is to transform the input information that similar input data is transformed into similar output vectors, and dissimilar data is transformed into output vectors that are significantly different.

The layers of the Siamese neural network act as a transformation function that focuses on the key features that determine the differences between the input data. This makes it possible to create distinctive output vectors even for input data with a high degree of similarity, such as ECG signals.

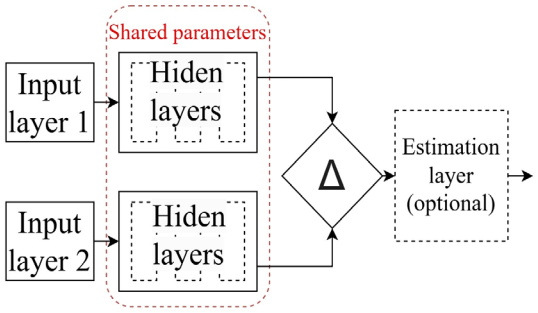

Fig. 1 Architecture of a classical Siamese neural network

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After processing the data by layers of the Siamese network, the resulting vectors are estimated using a similarity metric (*delta function*) [14]. In most cases, simple delta functions are used, such as Euclidean distance or cosine similarity, which provide a scalar output. However, sometimes the delta function can be expressed by combinations of several metrics. In this case, an additional layer can be used to assess the degree of difference, which decides on the similarity of the output vectors.

The hidden layers of a Siamese neural network can have different architectures depending on the task. For example, Convolutional layers are used to process two-dimensional data, and recurrent layers are used to analyse time sequences.

Convolutional layers of neural networks use specialised filters (*Convolutional kernels*) to extract morphological features from the signal, which allow analysing the signal at different levels of detalisation [15]. Convolutional have the following parameters: 1) The Convolution kernel is a small matrix that moves over the input signal, calculating the scalar product between the kernel nodes and the corresponding parts of the signal. 2) Stride is the parameter that determines the number of positions of the Convolution kernel shift during each movement along the input signal. 3) Padding is parameter that determines the addition of a frame of zeros or other values around the boundaries of the input signal to preserve the dimensionality of the output signal or to ensure that the kernel correctly covers the entire input space. The correct choice of these parameters determines how detailed the features will be extracted from the input data. The choice of kernel size affects the ability of the model to detect features at different scales. Increasing the stride can lead to information loss, but at the same time, it reduces the computational complexity and dimensionality of the data.

B. *Overview of the data for training and testing the neural network*

To test the developed model, the database "PTB-XL, a large publicly available electrocardiography dataset" was chosen as the training data, which contains about twenty-two thousand clinically recorded ECGs in 12-lead from 18869 patients [16]. Each record is approximately 10 seconds long. Although the database includes about 70 different pathological conditions of the cardiovascular system, only 20 of them contain a sufficient number of records to train neural networks. The following classes contain the largest number of records: Normal ECG, myocardial infarction, atrial fibrillation, left ventricular hypertrophy, left and right bundle branch block, atrial and ventricular extrasystoles. The ECG signals of this database are presented with 16-bit ADC resolution and 500 Hz sampling frequency, which makes it possible to use HR ECG methods to detect VLP and ALP.

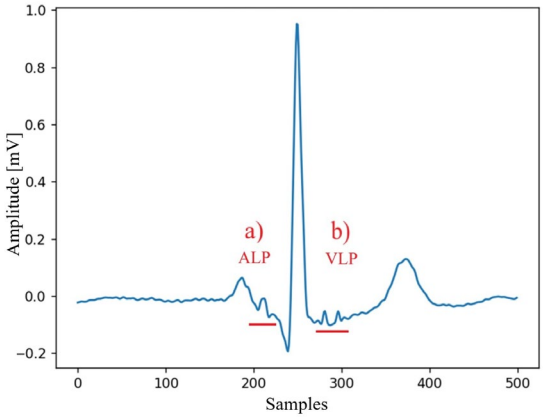

Fig. 2 An example of a cardiac cycle with atrial (a) and ventricular (b) late potentials.

For the study, the signals containing 18 types of cardiac arrhythmias were selected. In addition, the training dataset includes signals with 19 types of cardiac conditions that can cause or be accompanied by different types of arrhythmias. Such pathologies include various forms of myocardial hypertrophy, coronary heart disease, and heart attack [17]. The signals with existing VLPs and ALPs were also used for testing. Signals with VLP and ALP were obtained by superimposing artificially generated late action potentials on a normal ECG. The process of action potential propagation was modelled on the basis of the parallel conduction model [18]. In addition, normal ECG signals that did not contain any pathology were selected for the study. The example of a cardiac cycle with the existing VLP and ALP is shown in Fig. 2.

Due to the large number of selected subclasses, the amount of training data for each class varied greatly. For many diseases, the number of observations did not exceed 200. At the same time, classes with 2000 observations were also involved in the training process, including ECG signals corresponding to the normal state. To solve this problem, the input data were additionally balanced.

Firstly, to increase the number of observations in the samples with less than 500 records, data augmentation methods were applied [19], such as:

- Adding fragments of harmonic noise to the signal with a signal-to-noise ratio of 18-40 dB;
- Adding drift of isolines of different shapes;
- Adding physiological noise (breathing and muscle activity artefacts).

The parameters of harmonic noise, isoline drift, and physiological artefacts were adjusted to ensure that each altered ECG signal after augmentation was unique. This allowed to avoid repetition of the same modifications

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within the same disease class and to preserve the diversity of the data for further analysis. For classes with less than 150 observations, duplicate augmentation methods were used to double the sample size. For classes with 71 to 150 observations, the sample size was increased threefold, and for classes with 31 to 70 observations, the sample size was increased fourfold. This approach ensured proportional sample expansion depending on the initial size of the class data.

Secondly, for signals with pathologies that contained more than 1500 observations, neural network filtering was applied to remove records with a high level of noise or with the absence of a useful signal [20].

Therefore, classes with insufficient number of data were supplemented using augmentation methods. The classes with a large amount of data were reduced by removing noise signals, improving the overall quality of the training set.

C. *Preparation and pre-processing of data for NN training*

In accordance with the proposed complex method, twelve-channel signals of electrocardiography (ECG) are initially preprocessed. It is a necessary condition for improving the efficiency of model training. This stage reduces the dimensionality of the input data space, improves the structure of the input data, and improves their informativity, which leads to better signal processing by the neural network. Fig. 3 shows the main stages of signal pre-processing required for their input to the developed neural networks.

The first stage (Fig. 3) of signal pre-processing of the proposed complex method is noise removal. According to this stage, the first step of processing is input data filtering.

The signals from the twelve-channel ECG were processed using a fifth-order low-pass Butterworth filter with a cutoff frequency of 150 Hz to remove high-frequency noise. In turn, a third-order high-pass Butterworth filter with a cutoff frequency of 0.5 Hz was used to eliminate low-frequency noise [21]. In addition, the interference of the power grid in the ECG signals was also effectively removed using second-order digital notch filters configured for cutoff frequencies of 50 and 60 Hz with a quality factor of Q = 50 [21]. All signals were subjected to phase-neutral filtering, which ensured the preservation of the phase structure of the signal without distortion. [22].

At the second stage, to reduce the dimensionality of the input features, the twelve-channel ECG was transformed into the three-dimensional XYZ space using vectorcardiography methods [23].

Vectorcardiography is used to diagnose rhythm disturbances, myocardial damage and hypertrophy. To build a three-dimensional trajectory of the electrical axis of the heart, a Frank lead system is used, which provides accurate registration of signals in the frontal (*X*), sagittal (*Y*), and horizontal (*Z*) planes [24]. The standard twelve-lead system records the electrical activity of the heart in the frontal and horizontal planes, while the Frank system provides a more accurate analysis in the sagittal plane [25]. To obtain three-dimensional information, transformation methods are being developed to convert signals from the standard ECG lead system to the Frank lead system using linear transformation matrices [26]. This makes it possible to build three-dimensional models of cardiac electrical activity without using specialised equipment.

For a standard twelve-lead ECG, if one time sample of the signal is a vector with dimension of [12x1], then the three-dimensional representation of this sample in the Frank's lead system could be computed as a matrix product:

$$XYZ_{[3\times1]} = P_{[3\times12]} \cdot ECG_{[12\times1]},$$

where *P* is the linear transformation matrix.

The linear transformation matrix used to convert ECG signals from the standard lead system to the Frank's orthogonal lead system is shown below (Table 1).

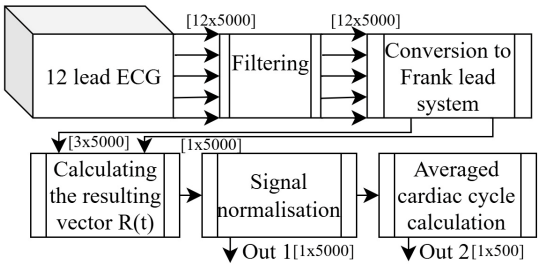

Fig. 3 Stages of preparation and pre-processing of the ECG signal for application in the developed neural networks

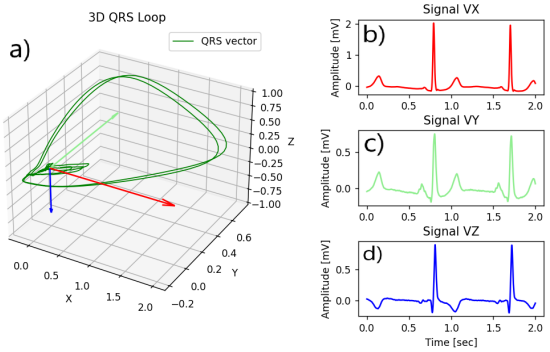

Fig. 4 Vectorcardiogram according to the Frank's lead system, vector of electrical activity of the heart in three-dimensional space (a), lead VX (b), lead VY (c); lead VZ (d).

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TABLE 1 MATRIX OF LINEAR TRANSFORMATIONS FROM STANDARD TO FRANK'S LEAD SYSTEM [26]

Lead	I	II	III	aVR	aVL	aVF
X	0.63	0.24	-0.40	-0.43	0.52	-0.08
Y	-0.24	1.07	1.30	-0.42	-0.77	1.18
Z	0.06	-0.13	-0.19	0.04	0.13	-0.16
	V1	**V2**	**V3**	**V4**	**V5**	**V6**
X	-0.52	0.04	0.88	1.21	2.13	0.83
Y	0.16	0.16	0.10	0.13	0.13	0.08
Z	-0.92	-1.39	-1.28	-0.60	-0.09	0.23

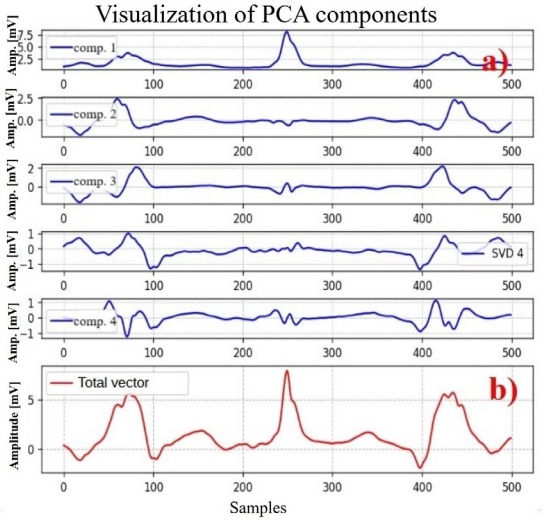

Fig. 5 Formation of a feature vector of signals with pathology using PCA. PCA decomposition vectors of 100 averaged cardiac cycles (a), the sum of the first five PCA decomposition vectors (b).

At the third stage, having a three-dimensional representation of the ECG signal, the resulting vector $R(t)$ can be obtained:

$$R(t) = \sqrt{X(t)^2 + Y(t)^2 + Z(t)^2},$$

where $X(t)$, $Y(t)$, $Z(t)$ are projection of a three-dimensional ECG on the *X, Y, Z* axis.

The use of this approach in the developed method makes it possible to convert a multidimensional, multichannel ECG signal into a three-dimensional representation or a one-dimensional resultant vector. This significantly reduces the dimensionality of the training data without significant loss of diagnostic information. Although such a representation may be difficult for doctors to understand, it may be quite sufficient for a neural network, since the resulting three-dimensional representation or resulting vector $R(t)$ compactly reflects the components of the multichannel ECG.

The next stage of signal preprocessing for the proposed complex method was the normalisation of the resulting feature vectors obtained for each observation [27]. This procedure was carried out to ensure scale consistency of the data, increase the model's resistance to variability of input parameters, and improve the convergence of the neural network training process. The resulting vectors were normalised by scaling the signals relative to R-peaks. In this case, the amplitude of the R-peak of the signal was adjusted to 1 mV.

At the final stage of signal processing, an averaged cardiac cycle was constructed. The averaged cardiac cycle is one of the tools of the ECG HR, which allows to obtain a QRS complex with a significantly lower noise level [28]. The use of the averaged cardiac cycle allows for a more detailed analysis of low-amplitude signal components, such as VLP, ALP, which can be useful for detecting life-threatening arrhythmias at early stages. To construct an averaged cardiac cycle, the ECG signal was segmented into one-second fragments with R-peak synchronisation. At the next step, the obtained fragments were superimposed on each other and averaged. Thus, for each resulting ECG signal vector of 5000 samples, an averaged cardiac cycle of 500 samples and one second duration was constructed.

Thus, the normalised resultant vector and the generated averaged cardiac cycle were used as input data of the neural network. This approach made it possible to preserve the information in the time domain obtained from a long-term ECG signal, while also providing a more accurate analysis of the cardiac cycle morphology due to the shorter but more detailed representation of the signal in the form of an averaged cardiac cycle.

D. Construction a feature vector of signals with pathologies for Siamese neural network

For training, the Siamese neural network requires the availability of reference signal samples for each pathology. Building such samples is also one of the key stages of the developed method.

Since the morphological features of ECG pathologies can differ between patients, so it is very difficult to extract a reference representation for training a Siamese neural network. To identify the main pathological features, it is necessary to use a sample of ECG signals, but the peculiarity of the architecture of Siamese neural networks requires the presence of identical input vectors for comparison. Therefore, principal component analysis (PCA) was applied to solve this problem. This statistical method is aimed at extracting the vectors that explain the largest part of the variation in the input data (*principal components*). The application of the PCA method makes it possible to obtain a feature vector containing information that reflects the common characteristics of ECG signals from patients with pathology [29].

The sum of the first five PCA decomposition components was used to form the feature vector (Fig. 5). Each principal component is dimensioned in millivolts because it is a weighted linear combination of the original ECG signals which are also expressed in the same units. This decomposition was performed separately to

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the resulting ECG vector and the constructed averaged cardiac cycles. As a result, a feature vector of signals with pathology was obtained for training (Fig. 6 c, d). Since the Siamese neural network is not aimed at memorising disease features like classical neural networks, but focuses on assessing the similarity between the signal under study and the reference feature vector, such vectors can be generated based on only 100 ECG records with pathology. Using PCA to build a feature vector allows to obtain a vector that is visually similar to the ECG signal.

This allows to analyse the impact of key signal peculiarities on the classification results of a neural network. However, the use of the principal component analysis (PCA) method to generate a feature vector has limitations, as the first five principal components may not contain enough information to correctly identify signal changes with the existing pathology. Therefore, the choice of a construction method for pathological feature vector should take into account specific diagnostic characteristics of different leads.

Fig. 6 shows an example of the signals fed to the inputs of a Siamese neural network. Each input signal consists of two components: an averaged cardiac cycle (Fig. 6 a, c), which contains detailed information about the morphology of the cardiac cycle, and a fragment of the ECG signal (Fig. 6 b, d), which contains characteristics of the heart's electrical activity over a longer time interval which is important for detecting rhythm disturbances. The amplitude scale in the lower plot (c-d) differs from the upper (a-b) because it represents the signal reconstructed from the first five principal components after PCA. Despite the transformation, the resulting signal also remains millivolt unit, because PCA is a linear transformation applied to the original ECG signals. However, due to the concentration of variance in the first components, their summation may lead to amplitude amplification in the reconstruction compared to the original input signal shown in (a-b).

Such representation allows the neural network to combine an accurate analysis of the shape of individual cardiac cycles with the features of a long-term ECG signal, which helps to improve the accuracy of cardiovascular disease diagnosis, in particular, the identification of arrhythmias and other pathological conditions at early stages.

Although PCA effectively reduces the dimensionality and allows to build aggregated representations from a small number of pathological ECG signals, it has a number of limitations. PCA captures global variance, which does not always reflect diagnostically significant features, such as artefacts or high amplitude signal components can produce high variance and predominate in PCA decomposition, at the same time, weakly expressed pathological features such as late potentials can have low variance and therefore may be missed in the low number of components. Since PCA operates with linear combinations of data, components with nonlinear patterns between ECG elements may be lost or poorly taken into account, especially when a limited number of principal components are used to form the representation (as in our case).

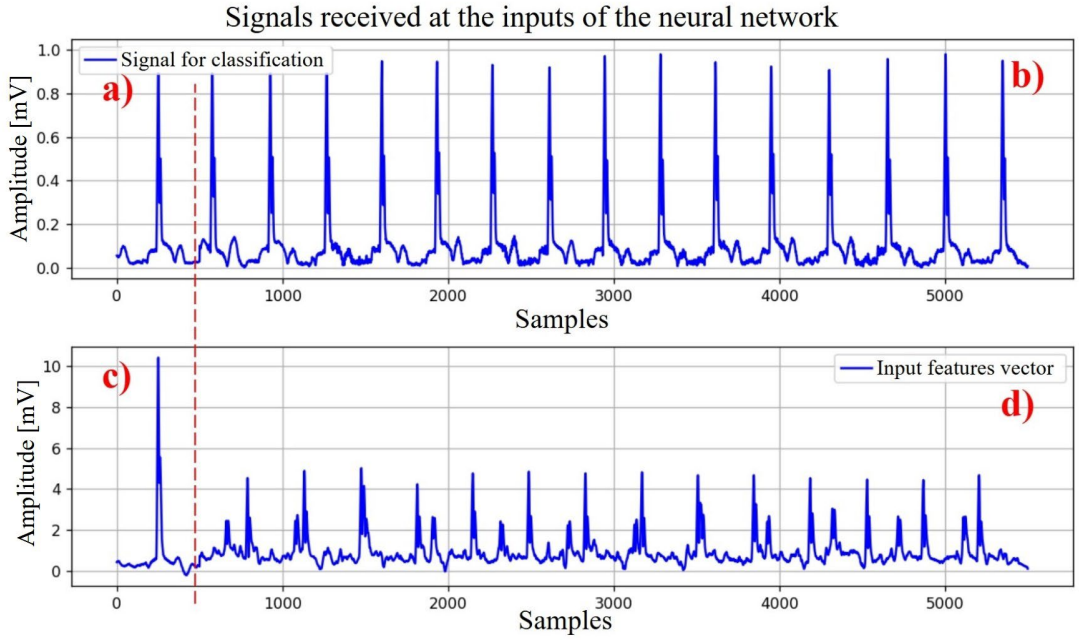

Fig. 6 An example of an input signal vector and feature vector of signals with pathology, averaged cardiac cycle (a), the resulting ECG signal vector (b), the result of PCA decomposition of 100 averaged cardiac cycles with pathology (c), the result of PCA decomposition of 100 input feature vectors with pathology (d).

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One possible way to improve the feature vector extraction quality is combining PCA with nonlinear dimensionality reduction methods or use neural network-based features vectors extraction, for example, using autoencoder.

E. Evaluation of neural network training quality

The following measures were used to assess the quality of neural network training: sensitivity, specificity, and overall classification accuracy. They provide a formalised characterisation of the ability of the NN model for correct recognition of disease classes, which is a key aspect of analysing its generalisation ability.

True Positive Rate (*TPR*) is the measure that reflects the proportion of correctly identified positive cases among all real positive instances, is calculated as:

$$TPR = \frac{TP}{TP + FN},$$

where *TP* (*True Positives*) is the number of correctly classified positive observations; *FN* (*False Negatives*) is the number of positive observations that were mistakenly classified as negative.

The true negative rate (*TNR*) is a measure that reflects the ability of a classifier to correctly identify negative instances among all objects belonging to a negative class. It is calculated by the formula:

$$TNR = \frac{TN}{TN + FP},$$

where *TN* (*True Negatives*) is the number of correctly classified negative observations, *FP* (*False Positives*) is the number of negative observations that were mistakenly assigned to the positive class.

Overall Accuracy (*ACC*) is an integral measure of classification quality that determines the proportion of correctly classified instances among all available objects. It is calculated by the formula:

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}$$

III. Development of Siamese neural networks models for classification of ECG signals with signs of arrhythmias using a limited amount of training data.

A. Development of a Siamese neural network model for VLP and ALP classification

At the initial stage of the study, the ability of the Siamese neural network to recognise a limited number of signals with the same type of pathology was assessed. This approach made it possible to preliminarily determine the effectiveness of the developed method for classifying ECG signals with cardiovascular pathologies. For testing, ECG signals with available late ventricular and atrial potentials were selected. Thus, the Siamese neural network was used to recognise normal ECGs, ECGs with VLPs, ECGs with ALPs, and ECG signals with VLPs and ALPs simultaneously.

In order to detect late ventricular and atrial potentials, the first Siamese neural network model was developed (Fig. 7). To train the neural network to recognise VLPs and ALPs, only the first 500 samples of the input signal, corresponding to the averaged cardiac cycle of the resulting ECG vector, were used.

For Siamese NN training, the backpropagation algorithm was applied, which adjusts the network's weights based on gradient descent. Adam (Adaptive Moment Estimation) was selected as the optimizer, combining the advantages of Adagrad and RMSprop methods. Adam adaptively adjusts the learning rate for each parameter by utilizing the first moment (the estimate of the mean gradient) and the second moment (the estimate of the mean squared gradient). This approach ensures stable weight updates even in complex nonlinear spaces. The main advantages of this optimizer are rapid convergence, efficient handling of noisy gradients, and the capability to avoid local minima, which contributes to the generalization ability of the model.

To train the NN, 3200 ECG records were selected, 800 for each of the four diagnostic classes. Reference feature vectors of signals with pathologies were generated for comparison from 100 randomly selected ECG signals with VLP and ALP. The training results of the first Siamese neural network model were compared with the training results of the specialised ECGnet architecture, which was trained on the same training data set. For each neural network, the batch size was chosen in the amount of 100 records, and training was performed for 100 epochs.

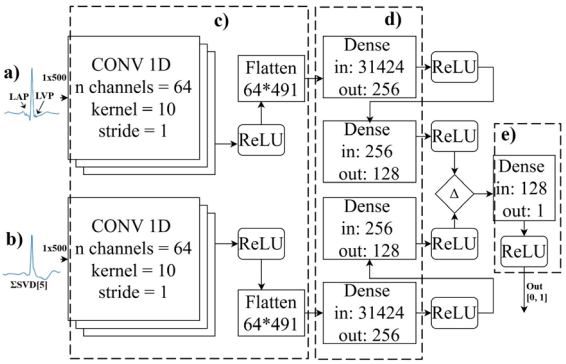

Fig. 7 Siamese neural network for VLP and ALP classification, averaged cardiac cycle of the signal under study (a), feature vector of signals with pathology (b), convolutional layers of the neural network (c), fully connected layers of the neural network (d), output layer (e).

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B. *Siamese neural network training results for VLP and ALP classification*

The results of training a Siamese neural network to detect ECG signals with pathological low-amplitude components, namely VLP and ALP, are shown in the Table 2.

From the analysis of Table 2, it can be concluded that the first Siamese NN model classification accuracy for the classes of normal, VLP, ALP, and VLP+ALP is higher than the accuracy achieved after training by the specialised ECGnet NN. The evaluation of the sensitivity and specificity measures showed that for the disease classes, the specificity significantly exceeds the sensitivity. This indicates the difficulty of recognising low-amplitude signal components, namely VLP and ALP, by neural networks. To eliminate this problem, it is necessary to apply additional methods of data pre-processing. At the same time, the use of the developed Siamese architecture leads to an increase in sensitivity, which confirms its effectiveness for the diagnosis of cardiovascular pathologies, in particular those characterised by low-amplitude features. Thus, the proposed Siamese architecture has the potential for application, especially in cases of diagnosis when comparing weakly expressed pathological signals changes.

C. *Development of a Siamese neural network models for arrhythmia classification*

For the multi-class classification task, in case of a lack of training data, a second Siamese neural network with a larger number of layers was developed.

The transformed ECG signal received from the patient was fed to one input of NN, and the feature vector of signals with the pathology under study was formed to the other input. The model was trained using different feature vectors for the same pathology. In the neural network under consideration, different parts of the input vector are analysed by two sequences of layers. The first sequence is aimed at extracting features from the averaged cardiac cycle. The second sequence extracts features from an ECG vector of ten seconds duration. In each sequence, the first Convolutional layers process the input signal, extracting features at different levels of detalisation, which allows for more efficient analysis of its structure and dynamic characteristics. In the subnetwork that processes the ECG vector, the first layer is the Pulling layer, which reduces the dimensionality of the input data from 5000 samples to 1000. This layer works as a resampling unit with the selection of the maximum coefficients of the Convolutional layer of the NN. After the Convolutional layers, both subnetworks have a Flatten layer that converts the multi-channel Convolutional result into a single-channel sequence for feeding to the fully connected neuronal layer.

TABLE 2 COMPARISON OF THE CLASSIFICATION QUALITY MEASURES OF THE SIAMESE NEURAL NETWORK AND THE ECGNET NETWORK IN THE VLP AND ALP RECOGNITION TASK

		Norm	VLP	ALP	VLP + ALP
Siamse net	***TPR***	98%	63%	52%	42%
	TNR	99%	90%	87%	100%
	ACC	98%	83%	78%	95%
ECG net	***TPR***	84%	32%	24%	34%
	TNR	87%	85%	87%	91%
	ACC	86%	71%	68%	86%

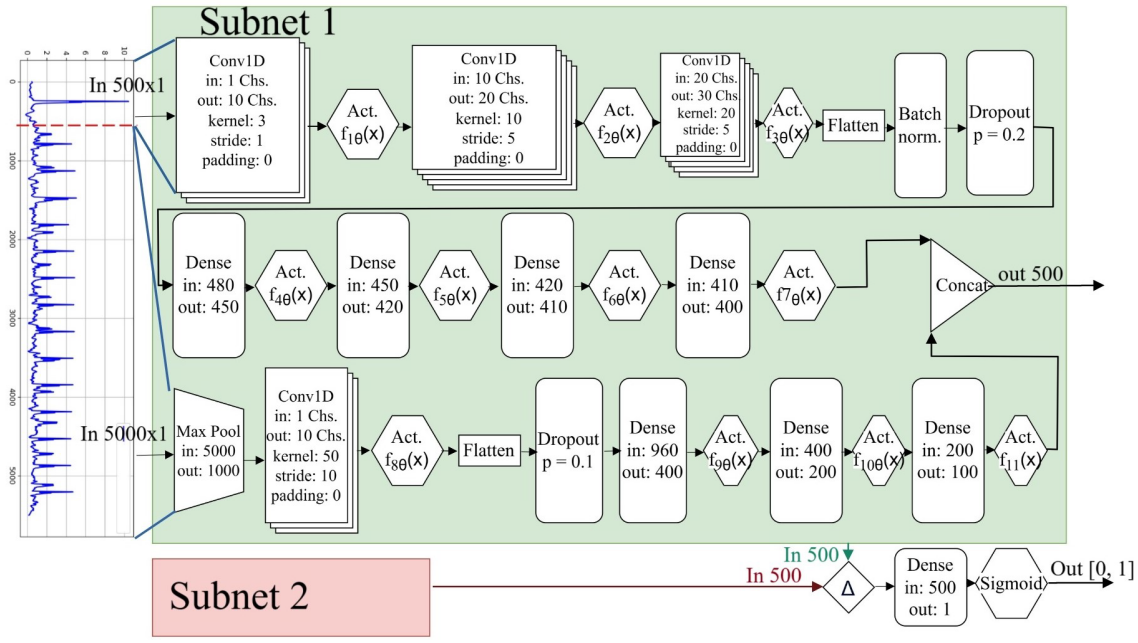

Fig. 8 Architecture of the designed Siamese neural network for arrhythmia classification

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Also, the subnetwork that processes the averaged cardiac cycle has a batch normalisation layer to increase the stability of the coefficients after the data has passed through many Convolution layers. Both subnetworks use a Dropout layer that disables 10% to 20% of random neurons during training. These layers are used to increase the generalisation power of the model and reduce possible overfitting. Each subnetwork is ended by several fully connected layers that sequentially reduce the number of output features. After passing through both subnetworks, the resultant vectors of 500 samples are generated and compared using a delta function that estimates the distance between them. The last fully connected layer used after the delta function determines the distance between analysed ECG vector and the feature vector of signals with pathology. The output of the last layer is 1 if the distance is small (pathology is detected) and 0 if the distance is large (the desired pathology is not detected).

D. The Siamese neural network training results for arrhythmia classification

Table 3 shows the results of classifying ECG signals with pathologies using the developed second Siamese neural network model. The table shows that the size of the data in each class does not exceed 2000, and the sample size for some pathologies is less than 200. To compare the classification results, the architecture of the specialised deep neural network ECGnet for ECG signal classification was chosen [12]. The ECGnet network was trained on the same training data as the developed Siamese NN. The difference was only in the output data format. The ECGnet neural network returned the result in the form of a vector of 37 elements in the one-hot encoding format. In turn, the developed neural network was trained to detect the similarity of the ECG signal under study and the feature vector of signals with pathology, which was built on the basis of 100 pathological ECG records. Each network was trained for 100 epochs, with a batch size of 200. The learning rate was set to $\eta = 0.001$. Both neural networks were tested on identical test data.

The analysis of Table 3 shows that for almost every pathology, the developed NN is more accurate than the ECGnet network. The average classification accuracy of ECG signals with pathologies was 64% for the ECGnet network and 74% for the developed Siamese neural network. The proposed Siamese architecture significantly improves the quality of pathology classification based on ECG signals. For samples with more than 1000 records, an improvement of 19% is observed for "Left anterior branch block". For samples with less than 1000 records, was obtained the improvement of 28% for "Ischemia in the anterolateral leads". For a training set of less than 200 records, an improvement of 19% was observed for "Lateral Myocardial Infarction". The overall average improvement in the accuracy of detecting VLP and ALP was 9%. Thus, the developed NN architecture also shows better results for detecting ECG signals with pathological low-amplitude components. It is relevant to note that the classification accuracy of VLP and ALP is about 60 %. This accuracy can be explained by the fact that other pathologies in the dataset have more expressive features, which in turn have a greater impact on the weighting coefficients of the neural network.

To solve this problem, it is necessary to additionally use methods for extracting low-amplitude ECG components. In addition, among the obtained results, there were classes of diseases whose classification accuracy was low, both using the developed neural network and ECGnet. Low classification accuracy is observed mainly in the detection of myocardial infarction and coronary heart disease. To detect these cardiac conditions, it is necessary to analyse the amplitudes of QRS complex peaks in different leads. The calculation of the resulting ECG vector based on the three-dimensional XYZ representation smoothes out amplitude differences in peaks, which makes it difficult to detect cardiomyopathies and ischemic disorders. To improve the accuracy of ECG signal classification for this type of pathology, it is better to use the XYZ representation of the ECG rather than the resultant vector.

It should be noted that Table 3 presents ECG signals with pathologies for which high classification accuracy is observed even with a limited sample size. These are mainly classes of pathologies characterised by severe rhythm disturbances, in particular, "Supraventricular tachycardia". The presence of clearly defined electrocardiographic signs makes such pathologies easier to identify by the neural network, which improves the accuracy of their diagnosis.

Compared to traditional classification approaches that directly compare the input ECG signals with diagnostic labels, the proposed method based on comparing the signal with the reference feature vector is less dependent from balanced data sets or high amount of training data. However, its accuracy may be lower in cases where pathologies have common or low-amplitude features. The comparative results between the classical approach based on ECGnet and the proposed Siamese neural network method on the mixed PTB-XL dataset are presented in Table 3. As shown in Table 3, the model performs well for pathologies with clear patterns (for example, 96% accuracy for supraventricular tachycardia), but provides limited improvement for complex diagnoses, such as ischemia in inferolateral leads or myocardial infarction, where the patterns are less clear. These limitations may be the subject of further research.

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TABLE 3 COMPARISON OF THE ECG CLASSIFICATION ACCURACY FOR SIGNALS WITH PATHOLOGIES USING THE DEVELOPED SIAMESE NEURAL NETWORK AND ECGNET

ECG Signals with Pathology	Number of Observations	ECGnet Accuracy	Developed Network Accuracy	ECG Signals with Pathology	Number of Observations	ECGnet Accuracy	Developed Network Accuracy
Atrial extrasystole	383	52%	68%	*Right ventricular hypertrophy*	141	65%	83%
Atrial fibrillation	1197	73%	80%	*Voltage electrocardiographic criteria for left ventricular hypertrophy*	655	52%	62%
Sinus arrhythmia	686	50%	60%	*Left atrial overload/enlargement*	390	51%	64%
Sinus tachycardia	888	72%	87%	*Right atrial overload/enlargement*	281	79%	86%
Sinus bradycardia	517	64%	78%	*Non-specific ischemia*	918	59%	74%
Supraventricular arrhythmia	409	62%	77%	*Ischemia in anterolateral leads*	607	50%	78%
Supraventricular tachycardia	149	99%	96%	*Ischemia in inferior leads*	204	51%	58%
Paroxysmal supraventricular tachycardia	160	99%	96%	*Ischemia in inferolateral leads*	190	53%	56%
Bigeminy of unknown origin	167	91%	82%	*Ischemia in anteroseptal leads*	160	51%	71%
Ventricular extrasystole	920	72%	78%	*Inferior myocardial infarction*	1532	51%	63%
First-degree AV block	710	51%	66%	*Anteroseptal myocardial infarction*	1242	56%	71%
Complete right bundle branch block	462	64%	87%	*Anterior myocardial infarction*	336	51%	59%
Complete left bundle branch block	559	94%	88%	*Anterolateral myocardial infarction*	211	54%	68%
Incomplete right bundle branch block	757	53%	67%	*Inferolateral myocardial infarction*	403	50%	59%
Left anterior fascicular block	1038	53%	72%	*Lateral myocardial infarction*	169	50%	69%
Left posterior fascicular block	192	60%	72%	*Prolonged QT interval*	348	68%	87%
Wolff-Parkinson-White syndrome	239	90%	94%	*ST-T changes associated with ventricular aneurysm*	142	86%	87%
Prolonged PR interval	281	51%	57%	*Late atrial potentials*	800	50%	58%
Left ventricular hypertrophy	1431	56%	69%	*Late ventricular potentials*	800	50%	60%
Right ventricular hypertrophy	141	65%	83%	*Average model accuracy*		68%	72%

CONCLUSION

In this study, an approach is proposed to solving the problem of classifying ECG signals with cardiovascular pathologies using Siamese neural networks under conditions of limited amount of training data.

A complex method has been developed that combines high-resolution electrocardiography and vector cardiography methods, as well as Siamese neural networks, which makes it possible to improve the accuracy of cardiac arrhythmias classification. A peculiarity of Siamese NNs is the ability to compare the input ECG signal vectors and the generated feature vector of signals with pathology, which allows to effectively identify their differences, even with a limited amount of training data. To construct the reference vectors the transformation from the 12-lead system to the orthogonal Frank system, as well as the construction of the averaged cardiac cycle and the principal component analysis (PCA) method was used. This approach made it possible to create feature vectors of signals with pathologies using only 100 observations.

In this study, two models of Siamese neural networks for the analysis of ECG signals were developed. First model is focused on the detection of low-amplitude pathological features, such as VLP and ALP. The second model is designed for multi-class classification of 18 types of arrhythmias and 19 associated pathologies, including coronary heart disease, hypertrophy, and myocardial infarction.

The results of the study demonstrated that the proposed Siamese NN has higher accuracy compared to the specialised ECGnet network. In the task of VLP and ALP detection, the first NN model exceeded the accuracy of the classic approach by 10%, while reducing the number of false-negative predictions. The second NN model, designed for multi-class signal classification, improved the classification accuracy by 10% on average, and for individual classes, such as ischemic changes in the anterolateral leads, the maximum improvement was 28%.

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The obtained results confirm the promising application of Siamese neural networks in the tasks of automated diagnosis of cardiovascular diseases, especially under conditions of insufficient amount of balanced training data. Further improvement of the method is possible by using additional transformations of input features to save more information about weakly expressed pathological changes in ECG signals, as well as by applying additional methods to intensify low-amplitude signal components. The developed complex method has the potential for implementation in modern automated cardiac diagnostic systems, particularly for detecting arrhythmias and other disturbances in the heart's electrical activity that are characterized by weak manifestations in ECG.

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Моделі сіамських нейронних мереж для класифікації серцевих аритмій за умов нестачі тренувальних ЕКГ сигналів

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***Анотація*—Стаття присвячена створенню моделей сіамських нейронних мереж для класифікації ЕКГ-сигналів, що відображають серцево-судинні патології, зокрема аритмії, в умовах обмеженої кількості тренувальних даних. Проблема дефіциту навчальних зразків у машинному навчанні для діагностики серцевих захворювань пов’язана з великою різноманітністю патологічних станів і недостатньою інформацією для окремих класів у відкритих медичних базах даних. Дослідження спрямоване на розробку комплексного методу, який ґрунтується на поєднанні методів електрокардіографії високого розрізнення та векторкардіографії з архітектурами та методами навчання сіамських нейронних мереж, що дає можливість підвищити точність класифікації серцевих аритмій. Особливість запропонованого метода, яка базується на здатності сіамських НМ до порівняння, полягає у виявленні та аналізі відмінностей між ЕКГ сигналом, що досліджується, та сформованим еталонним вектором ознак сигналів з патологією, що дозволяє ефективно ідентифікувати зміни сигналів навіть для тих захворювань, які обмежено-представлені в навчальному наборі даних. Крім того, для підвищення ефективності навчання був розроблений метод формування еталонного вхідного вектора ознак захворювання, який використовується сіамською нейронною мережею для порівняння. Застосування методу головних компонент (PCA) дозволило виділити ключові ознаки зі 100 ЕКГ-сигналів із патологіями, що сприяло створенню еталонного вектора ознак із мінімальною кількістю тренувальних зразків. Додатково для кожного вхідного ЕКГ-сигналу та еталонного вектора розраховувався усереднений кардіоцикл, що сприяло ідентифікації низькоамплітудних компонентів ЕКГ та особливостей QRS комплексу. Для реалізації розробленого комплексного методу використовувалася база PTB-XL, що містить 12-канальні ЕКГ-записи, класифіковані за 70 категоріями захворювань. Для зменшення впливу дисбалансу даних застосовано методи аугментації, а також методи попередньої обробки шляхом видалення зашумлених сигналів та вибіркове скорочення надмірно представлених класів. В рамках дослідження розроблено дві моделі сіамських нейронних мереж. Перша модель орієнтована на виявлення низькоамплітудних патологічних компонент ЕКГ сигналів, зокрема пізніх потенціалів передсердь та шлуночків. Друга модель, призначена для класифікації 18 типів аритмій і 19 супутніх патологій, таких як ішемічна хвороба серця, гіпертрофія та інфаркт міокарда. Ефективність запропонованих моделей НМ була оцінена шляхом порівняння з мережею «ECGnet» у задачі розпізнавання пізніх потенціалів передсердь і шлуночків. Перша модель перевищила точність «ECGnet» у середньому на 10% та зменшила ймовірність хибнонегативних прогнозів. Друга модель НМ для багатокласової класифікації, яка охоплювала 37 діагностичних класів з рідкісними захворюваннями, що мають менше, ніж 200 спостережень, перевищила середню точність «ECGnet» на 10%, досягаючи максимального приросту в 28%. Отримані результати дозволяють окреслити подальші шляхи вдосконалення комплексного методу. Зокрема, підвищення точності класифікації ЕКГ сигналів з патологіями можливе шляхом використання додаткових перетворень вхідних ознак та методів підсилення низькоамплітудних компонент сигналу.**

Ключові слова — електрокардіографія; сіамські нейронні мережі; пізні потенціали шлуночків; пізні потенціали передсердь; серцева аритмія; векторкардіографія; сингулярний розклад.