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EXPRESS METHOD OF BIOMETRIC PERSON AUTHENTICATION BASED ON ONE CYCLE OF THE ECG SIGNAL

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Summary. *The article is devoted to an express method of biometric authentication of a person based on an electrocardiogram (ECG). The method is characterized by high accuracy (efficiency) of authentication of a person based on only one cycle of its ECG. Such characteristics as Accuracy, Balanced Accuracy and F1-score on average are not lower than 96.1% for such binary classifiers as k-Nearest Neighbors, Linear SVM, Decision Tree, Random Forest, Multilayer Perceptron, Adaptive Boosting, Naive Bayes and Statistical Interval Classifier. The research utilized the Combined Measurement of ECG, Breathing, and Seismocardiograms database, which features data from 20 healthy people. A method of constructing confidence intervals for ECG cycles has been developed, which is based on the rhythm-adaptive statistical estimation of the mathematical expectation and the standard deviation of the ECG signal. The method of constructing confidence intervals is based on the functioning of the Statistical Interval Classifier in the system of biometric authentication of a person. The Statistical Interval Classifier has the lowest time computational complexity among the 8 studied classifiers, which justifies its use in portable biometric authentication systems that have negligible computing resources.*

Key words: *biometric authentication, electrocardiogram signal, cyclically correlated random process, signals normalization, signals classification.*

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Introduction. Biometric authentication plays a crucial role in information security, more so today with the growing emphasis on protecting personal data and accurately identifying individuals online. This method is based on the use of unique physiological or behavioral characteristics of an individual, which are difficult to fake. Biometric authentication includes such types as: fingerprint scanning, facial recognition, retina scanning, hand geometry analysis, voice recognition, as well as more innovative methods like acoustic cardiac signal analysis and electrocardiogram (ECG) pattern analysis [1–6]. Each of these methods has its own advantages and limitations in terms of accuracy, reliability, user convenience, and resistance to forgery attempts. Modern technologies allow the development of increasingly accurate and reliable biometric authentication systems, facilitating their widespread implementation in various areas – from access control and security systems to mobile applications and online services. An important aspect is also ensuring the confidentiality and security of biometric data processing, as they belong to the category of particularly sensitive information.

The evolution of ECG acquisition techniques in biometric research has been marked by significant advancements, particularly aimed at enhancing the acceptability of ECG as a biometric trait. Early studies primarily leveraged the standard 12-lead configuration for developing biometric algorithms [7, 8]. Over time, there was a notable shift toward the selective use of specific leads, especially Lead I and Lead II, favored for their higher acceptability due to wrist electrode placement [9–11]. Recent developments have further expanded this scope by

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integrating ECG acquisition into wearable technologies and everyday objects, paving the way for more versatile and user-friendly biometric solutions [12, 13].

Research in ECG-based biometric authentication, as indicated by numerous studies [1–3, 9, 14], primarily varies in terms of the features extracted and the machine learning classifiers employed. A significant portion of these studies have implemented robust classifiers like K-nearest neighbors (K-NN) [15, 16], Linear Discriminant Analysis (LDA) classifiers [17], Support Vector Machine (SVM) classifiers [16], and Random Forest (RF) classifiers for recognizing biometric traits through ECG. In the paper «A neural network to identify human subjects with electrocardiogram signals» [18], the exploration of ECG biometric authentication was conducted using a multi-layer perceptron (MLPNN) classifier, with an emphasis on discrete wavelet transform (DWT) features. Another paper «Wavelet distance measure for person identification using electrocardiograms» [19] delved into the effectiveness of biometric ECG, particularly focusing on non-fiducial features, and utilized the nearest centre classifier, a specific type of nearest neighbor classifier, for network training. The paper «Investigation of human identification using two-lead ECG signals» [20] implemented an SVM classifier equipped with a Gaussian RBF kernel and discrete wavelet features, managing to achieve a remarkable 99.60% accuracy rate using single-day ECG signals derived from two channels.

Previous research in the field of biometric authentication using ECG signals has made significant progress, but it shows some limitations that require further research. A problem that is constantly revealed in these studies is the insufficient accuracy of the existing approaches. This disadvantage is particularly pronounced during adaptation to variable rhythms, which is a critical aspect given the dynamic nature of ECG signals. The lack of rhythmic adaptation in current methodologies creates a challenge to achieve consistent and reliable biometric authentication.

The purpose of this paper is to solve these problems by developing an efficient express method of human biometric authentication based solely on a single cycle of the ECG signal. This approach aims to improve the accuracy and adaptability of ECG-based biometric systems, providing a fast and reliable authentication process. Focusing on a single ECG cycle, the proposed method aims to provide a more rational and cost-effective solution without compromising the accuracy and reliability required for biometric authentication.

Models and technology of processing of ECG signals in systems of biometric authentication of a person. The paper proposes the following sequence of stages of ECG signal processing for the needs of biometric authentication. Figure 1 shows a generalized structural diagram showing the main stages of ECG signal processing in biometric personal authentication systems.

Figure 1. The generalized structural diagram showing the main stages of ECG signal processing in biometric personal authentication systems

The research utilized the Combined Measurement of ECG, Breathing, and Seismocardiograms (CEBS) database [21, 22, 23], which features data from 20 healthy people. For the authentication experiment, the focus was on the ECG signal from lead II. Selected patients for this study were 001-003, 005-010, and 013. Each patient's 30-minute ECG recording was used for training and testing the classifiers. As an example, the first cycles of ECG from the CEBS for person 1 and for person 2 are presented in Figure 2 and Figure 3.

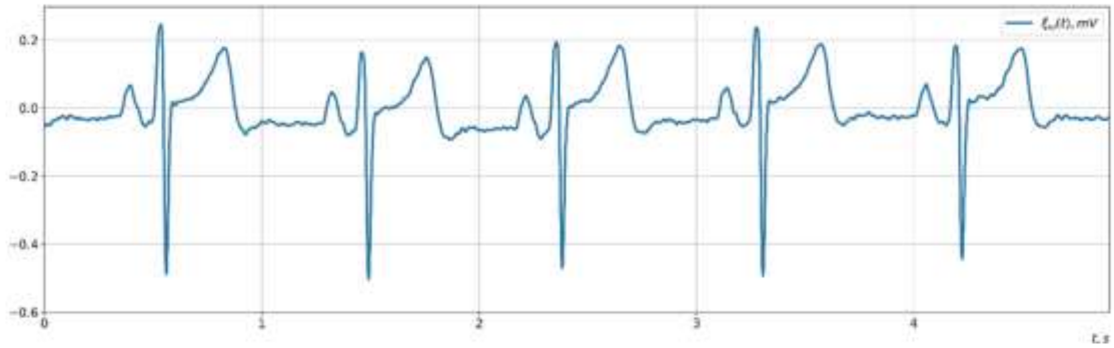


Figure 2. Graph of the first cycles of ECG for a conditionally healthy person 1

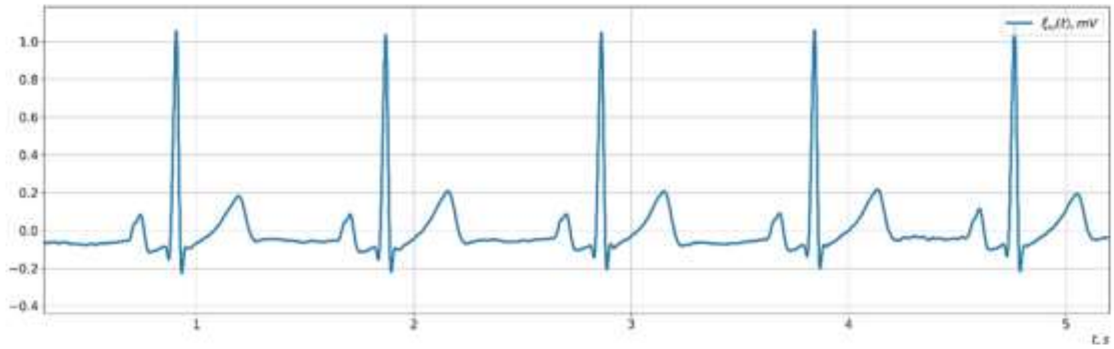


Figure 3. Graph of the first cycles of ECG for a conditionally healthy person 2

Procedures for training and testing classifiers require the formation of test and training samples from the ECG database. Let's briefly consider this procedure.

In order to formally display the ECG cyclical structure, ECG $\xi_i(\omega, t)$ for the i-th person can be presented as follows:

$$\xi_i(\omega, t) = \sum_{m=1}^{M} \xi_{i,m}(\omega, t)\,, \omega \in \boldsymbol{\Omega},\ t \in \boldsymbol{W}, \tag{1}$$

where $\boldsymbol{W}$ is the time domain of the ECG definition, M – number of registered cycles in ECG.

The random process $\xi_{i,m}(\omega, t)$ coincides (is identical) with a random process $\xi_i(\omega, t)$ on the area $\boldsymbol{W}_{i,m} = [t_{m-1}, t_m)$ that correspond to the m-th cycle of the ECG and which is equal to:

$$\xi_{i,m}(\omega, t) = \xi_i(\omega, t) \cdot I_{\boldsymbol{W}_{i,m}}(t),\ \omega \in \boldsymbol{\Omega},\ t \in \boldsymbol{W}, m = \overline{1, M}. \tag{2}$$

Function $I_{\boldsymbol{W}_{i,m}}(t)$ is indicator function

$$I_{\boldsymbol{W}_{i,m}}(t) = \begin{cases} 1,\ t \in \boldsymbol{W}_{i,m}, \\ 0,\ t \notin \boldsymbol{W}_{i,m}. \end{cases} \tag{3}$$

Time domain $\boldsymbol{W}$ can be represented as $\boldsymbol{W} = U_{m=1}^{M} \boldsymbol{W}_{i,m}$.

The result of ECG segmentation is obtaining a set of segments-cycles $\{\xi_{i,m}(\omega, t), m = \overline{1, M}\}$, which are set on such time domains $\{\boldsymbol{W}_{i,m}, m = \overline{1, M}\}$.

Figure 4 shows an example of segmenting a healthy patient's ECG into cycles.

For the purpose of forming uniform training and test samples from multi-cycle EEG for each cycle $\xi_{i,m}(\omega,t)$ static shift operator $\boldsymbol{G}_{s_{i,m}}[\cdot]$ and a static scaling operator $\boldsymbol{G}_{\alpha_{i,m}}[\cdot]$ are applied, which ensure the transfer of this cycle from the area $\boldsymbol{W}_{i,m}$ in unit interval $[0,1]$, namely:

$$\tilde{\xi}_{i,m}(\omega,t) = \boldsymbol{G}_{s_{i,m}}\left[\boldsymbol{G}_{\alpha_{i,m}}\left[\xi_{i,m}(\omega,t)\right]\right] = \xi_{i,m}\left(\omega,\alpha_{i,m}\cdot t + s_{i,m}\right),$$

$$t \in \boldsymbol{W}_{i,m} = \left[t_{i,m-1}, t_{i,m}\right), m = \overline{1,M}, \tag{4}$$

where the coefficients of static shift $s_{i,m}$ are defined according to the expression

$$s_{i,m} = -t_{i,m-1}, \tag{5}$$

and the coefficients of static scaling $\alpha_{i,m}$ are defined according to the expression

$$\alpha_{i,m} = \frac{1}{t_{i,m}-t_{i,m-1}}. \tag{6}$$

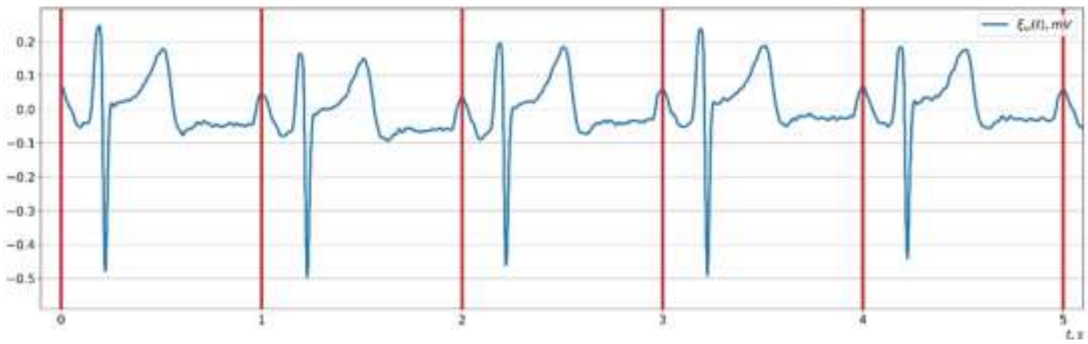


Figure 4. ECG and the result of its segmentation into cycles

As a result of such shifting and scaling transformations of ECG cycles, a sequence of normalized cycles $\left\{\tilde{\xi}_{i,m}(\omega,t), m = \overline{1,M}\right\}$ is formed.

For the purpose of training and testing classifiers, it is necessary to form test and training samples for each person for whom the ECG is contained in the CEBS database. The sample for the i-th person must be balanced and include a set of ECG cycles directly for this i-th person and a set of ECG cycles for other persons (not for the i-th person) from the CEBS database.

Thus, for the i-th person, the training sample is a sequence $\left\{LS_k(\omega,t), k = \overline{1,2\cdot M_1}\right\}$ (let's accept $M_1 = \frac{2}{3}M$), the elements of which are alternately selected from ordered sets $\left\{\tilde{\xi}_{i,m}(\omega,t), m = \overline{1,M_1}\right\}$ and $\left\{\tilde{\xi}_{G_i,l}(\omega,t), l = \overline{1,M_1}\right\}$. The set $\left\{\tilde{\xi}_{i,m}(\omega,t), m = \overline{1,M_1}\right\}$ is the set of the first M_1 normalized cycles that make up the ECG $\xi_i(\omega,t)$ for i-th person, and the set $\left\{\tilde{\xi}_{G_i,l}(\omega,t), l = \overline{1,M_1}\right\}$ is a set that includes M_1 normalized cycles from ECG signals for all persons from the CEBS base, except for the i-th person.

Similarly, a test sample is formed for the i-th person $\left\{TS_k(\omega,t), k = \overline{1,2\cdot(M-M_1)}\right\}$, the elements of which are alternately selected from ordered sets $\left\{\tilde{\xi}_{i,m}(\omega,t), m = \overline{M_1+1,M}\right\}$

and $\left\{\tilde{\xi}_{G_i,l}(\omega,t), l=\overline{M_1+1,M}\right\}$. The set $\left\{\tilde{\xi}_{i,m}(\omega,t), m=\overline{M_1+1,M}\right\}$ is the set of the last $M-M_1$ normalized cycles that make up the ECG $\xi_i(\omega,t)$ for the i-th person, and the set $\left\{\tilde{\xi}_{G_i,l}(\omega,t), l=\overline{M_1+1,M}\right\}$ is a set that includes $M-M_1$ normalized cycles from ECG signals for all persons from the CEBS base, except for the i-th person.

For each i-th person during binary classification in training and testing mode, the following two hypotheses H_0 and H_1 must be tested:

$$H_0\text{: } cycle\ \xi_i(\omega,t)\ does\ not\ belong\ to\ the\ ECG\ of\ the\ i-th\ person, \tag{7}$$

vs

$$H_1\text{: } cycle\ \xi_i(\omega,t)\ belongs\ to\ the\ ECG\ of\ the\ i-th\ person. \tag{8}$$

For the implementation of classifiers in the ECG-based authentication system, the scikit-learn library was employed. This versatile Python library is renowned for its efficacy in machine learning tasks. The range of classifiers used included k-Nearest Neighbors, Linear SVM, Decision Tree, Random Forest, Multilayer Perceptron, Adaptive Boosting and Naive Bayes. Each classifier was carefully parameterized to optimize its performance specifically for ECG data analysis, ensuring a robust and comprehensive approach to authenticate patients effectively using ECG signals.

In order to expand the set of possible classifiers, we will develop a method of biometric authentication of a person based on one of its ECG cycles, by using the method of confidence intervals. We will construct confidence intervals for cardiocycles, based on mathematical models of the ECG in the form of a cyclically correlated random process. According to the works [24–26], we will give the definition of the cyclically correlated random process of a continuous parameter.

Definition 1. The random process $\xi(\omega,t), \omega\in\boldsymbol{\Omega}, t\in\boldsymbol{R}$ is called the ***cyclically correlated random process of a continuous parameter***, if for it mathematical expectation $m_\xi(t)$ and autocovariance function $R_\xi^2(t_1,t_2)$ exists a such function $T(t,n), t\in\boldsymbol{R}, n\in\boldsymbol{Z}$, which satisfies the conditions (9)–(11) of the rhythm function, and there are following equalities:

$$m_\xi(t)=m_\xi(t+T(t,n)), t\in\boldsymbol{R}, n\in\boldsymbol{Z}; \tag{9}$$

$$R_\xi^2(t_1,t_2)=R_\xi^2(t_1+T(t_1,n), t_2+T(t_2,n)), t_1,t_2\in\boldsymbol{R}, n\in\boldsymbol{Z}. \tag{10}$$

The rhythm function $T(t,n), t\in\boldsymbol{R}, n\in\boldsymbol{Z}$ has the following properties:

1)
$$\begin{cases} T(t,n)>0\ (T(t,1)<\infty), t\in\boldsymbol{R}, if\ n>0, \\ T(t,n)=0, t\in\boldsymbol{R}, if\ n=0, \\ T(t,n)<0, t\in\boldsymbol{R}, if\ n<0; \end{cases} \tag{11}$$

2) for any $t_1\in\boldsymbol{R}$ and $t_2\in\boldsymbol{R}$, for which $t_1<t_2$, for function $T(t,n)$ a strict inequality holds:

$$T(t_1,n)+t_1<T(t_2,n)+t_2, \forall n\in\boldsymbol{Z}; \tag{12}$$

3) function $T(t,n)$ is the smallest in modulus $\left(|T(t,n)| \leq |T_\gamma(t,n)|\right)$ among all such functions $\{T_\gamma(t,n), \gamma \in \boldsymbol{N}\}$ which satisfy (11) and (12), namely:

$$|T(t,n)| = min_{\gamma \in \boldsymbol{N}}\{|T_\gamma(t,n)|, \gamma \in \boldsymbol{N}\}, t \in \boldsymbol{R}, n \in \boldsymbol{Z}. \tag{13}$$

The rhythm function $T(t,n)$ determines the law of changing the time intervals between the single-phase values of the cyclically correlated random process.

In many articles ECG signals are considered to be normally distributed random processes, which makes it possible to construct a confidence interval for each of its values based on rhythm-adaptive statistical estimates of mathematical expectation

$$\widehat{m}_{\xi_i}(t) = \frac{1}{M} \cdot \sum_{n=0}^{M-1} \xi_\omega\big(t + T(t,n)\big), t \in \boldsymbol{W}_{c_1}. \tag{14}$$

and standard deviation

$$\hat{\sigma}_{\xi_i}(t) = \sqrt{\frac{1}{M-1} \cdot \sum_{n=0}^{M-1}\left[\xi_i\big(t + T(t,n)\big) - \widehat{m}_{\xi_i}\big(t + T(t,n)\big)\right]^2}, t \in \boldsymbol{W}_{c_1}, \tag{15}$$

where $\boldsymbol{W}_1 = [0,1]$ – the area of definition of normalized ECG cycles.

The confidence interval that covers the ECG value for person i with a probability of 0.997 will look like this

$$\widehat{m}_{\xi_i}(t) - 3\hat{\sigma}_{\xi_i} \leq \xi_i(\omega,t) \leq \widehat{m}_{\xi_i}(t) + 3\hat{\sigma}_{\xi_i}(t), t \in [0,1]. \tag{16}$$

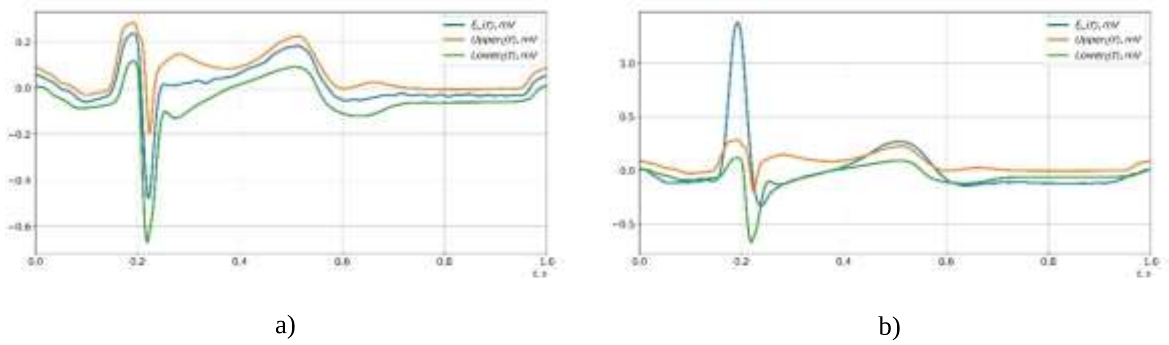
Figure 5 and Figure 5 show the confidence intervals for two persons, as well as the ECG cycles for these persons.

On the basis of constructed confidence intervals for normalized ECG cycles, we will develop a procedure for authenticating a person based on one cycle of an ECG signal, namely, we will develop a Statistical Interval Classifier (SIC). The essence of the classification procedure in this case is to choose one of the statistical hypotheses H_0 and H_1:

$$H_0: \xi_i(\omega,t) \notin \left(\widehat{m}_{\xi_i}(t) - 3\hat{\sigma}_{\xi_i}, \widehat{m}_{\xi_i}(t) + 3\hat{\sigma}_{\xi_i}\right), \tag{17}$$

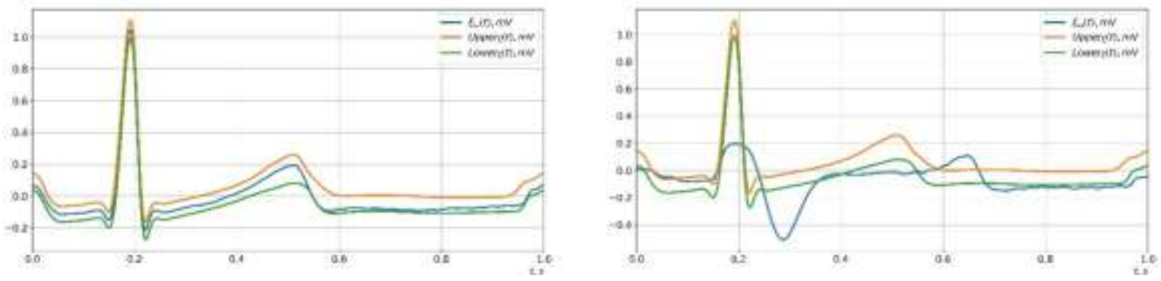
vs

$$H_1: \xi_i(\omega,t) \in \left(\widehat{m}_{\xi_i}(t) - 3\hat{\sigma}_{\xi_i}, \widehat{m}_{\xi_i}(t) + 3\hat{\sigma}_{\xi_i}\right). \tag{18}$$



a) b)

Figure 5. Confidence interval and one normalized ECG cycle of person 1 (a) and confidence interval of person 1 and one normalized ECG cycle of person 2 (b)



a) b)

Figure 6. Confidence interval and one normalized ECG cycle of person 2 (a)
and confidence interval of person 2
and one normalized ECG cycle of person 1 (b)

The decision making rule is based on calculation of parameter N_i – percentage (number) of hits $\xi_i(\omega, t)$ in the interval for the i-th person.

Decision making rule for SIC:

1) Reject H_0 and acceptance H_1 if $N_i > 95\%$,

2) Reject H_1 and acceptance H_0 if $N_i \leq 95\%$.

For SIC the training procedure consists in the rhythm-adaptive statistical estimation of the mathematical expectation and the standard deviation of the ECG signal, as well as in the construction of a confidence interval for a normalized ECG cycle.

Results of a computational experiment. The development prototype of the authentication software was conducted on a Linux-based operating system, which provided a robust and versatile platform suitable for high-level computing and data analysis. The software was built using Python 3.6.9, a choice guided by Python's simplicity and its extensive support for scientific computing. Several specialized libraries were utilized in the development process, each contributing significantly to the software's functionality:

– Pandas: This library was employed for data manipulation and analysis. It offers data structures and operations for manipulating numerical tables and time series, making it indispensable for handling the EEG dataset.

– NumPy: Known for its powerful N-dimensional array object, NumPy was a key component for numerical computations. It provided support for a wide range of mathematical operations, which are crucial in handling and processing EEG data.

– NeuroKit2: A specialized library for neurophysiological data processing, NeuroKit2 was used for its advanced features in processing and analyzing physiological signals, including EEG.

– Matplotlib: This plotting library was used for visualizing the data.

The combination of these tools and libraries, created a powerful environment for the development of software capable of performing accurate and efficient patient authentication using EEG data.

All eight classifiers were trained and tested for ten conditionally healthy persons whose ECG contains the CEBS database. The main characteristics of the effectiveness of biometric authentication and the time computational complexity of the algorithms for training and testing the classifiers are shown in Table 1 and Table 2 for person 1 and 2, respectively.

Table 1

The main characteristics of the effectiveness of biometric authentication and the time computational complexity of the algorithms for Person 1

	Classifier type							
	SIC	k-Nearest Neighbors	Linear SVM	Decision Tree	Random Forest	Multilayer Perceptron	Adaptive Boosting	Naive Bayes
Accuracy	0.976	0.999	0.999	1.0	0.995	0.990	1.0	1.0
Balanced Accuracy	0.976	0.999	0.999	1.0	0.995	0.990	1.0	1.0
F1 score	0.977	0.999	0.999	1.0	0.995	0.990	1.0	1.0
Training time (ms)	2.49	22.59	61.53	79787.54	387.64	42.90	3558.57	4936.56
Testing time (ms)	12.32	131.73	9.67	525.38	3.41	5.49	8.072	38.91

Table 2

The main characteristics of the effectiveness of biometric authentication and the time computational complexity of the algorithms for Person 2

	Classifier type							
	SIC	k-Nearest Neighbors	Linear SVM	Decision Tree	Random Forest	Multilayer Perceptron	Adaptive Boosting	Naive Bayes
Accuracy	0.970	0.999	0.999	1.0	0.997	0.964	1.0	0.999
Balanced Accuracy	0.971	0.999	0.999	1.0	0.998	0.964	1.0	0.999
F1 score	0.970	0.999	0.999	1.0	0.997	0.963	1.0	0.999
Training time (ms)	2.43	21.61	42.84	50887.81	287.67	47.79	3536.46	4949.71
Testing time (ms)	12.61	144.26	4.21	505.71	3.43	5.64	7.87	39.24

Table 3 shows the averages for 10 people the average main characteristics of the effectiveness of biometric authentication and the time computational complexity of the algorithms for training and testing the classifiers.

Table 3

The average main characteristics of the effectiveness of biometric authentication and the time computational complexity of the algorithms

	Classifier type							
	SIC	k-Nearest Neighbors	Linear SVM	Decision Tree	Random Forest	Multilayer Perceptron	Adaptive Boosting	Naive Bayes
Accuracy	0.964	0.999	1.0	1.0	0.996	0.987	1.0	0.999
Balanced Accuracy	0.962	0.999	1.0	1.0	0.996	0.987	1.0	0.999
F1 score	0.961	0.999	1.0	1.0	0.996	0.987	1.0	0.999
Training time (ms)	2.67	19.87	46.16	77604.12	332.66	46.36	3450.96	4595.05
Testing time (ms)	12.51	132.69	5.24	536.62	3.42	5.67	8.13	36.45

As can be seen from Table 1, Table 2, and Table 3, for all types of classifiers, a high efficiency of person authentication is observed for one ECG cycle. On the other hand, the classifiers differ significantly in terms of time computational complexity. The Statistical Interval Classifier has a negligibly small training time compared to other classifiers, which indicates its promising use in portable systems with limited computing resources.

Conclusions. In the article, an effective express method of biometric person authentication based on one cycle of the ECG signal was developed. The method is characterized by high efficiency of personal authentication, namely, such characteristics as Accuracy, Balanced Accuracy and F1-score on average are not lower than 96.1% for such binary classifiers as k-Nearest Neighbors, Linear SVM, Decision Tree, Random Forest, Multilayer Perceptron, Adaptive Boosting, Naive Bayes and Statistical Interval Classifier. It was established that in terms of computational time complexity the best classifier for the biometric authentication of a person based on one ECG cycle is the Statistical Interval Classifier, since the average training time of such a classifier is significantly less than the average training time of all other classifiers used in the study. Considering the results obtained in this work, it is promising to study other types of cardiac signals, for example, acoustic cardiac signals for biometric authentication of a person, as well as to study the effectiveness of various classifiers in the mode of biometric identification of a person.

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ЕКСПРЕС-МЕТОД БІОМЕТРИЧНОЇ АУТЕНТИФІКАЦІЇ ОСОБИ НА ОСНОВІ ОДНОГО ЦИКЛУ СИГНАЛУ ЕКГ

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Резюме. *Присвячено експрес-методу біометричної аутентифікації особи на основі електрокардіограми (ЕКГ). Метод характеризується високою точністю (ефективністю) аутентифікації особи на основі лише одного циклу її ЕКГ. Такі характеристики, як Accuracy, Balanced Accuracy та F1-score в середньому не нижчі за 96.1% для таких бінарних класифікаторів, як k-Nearest Neighbors, Linear SVM, Decision Tree, Random Forest, Multilayer Perceptron, Adaptive Boosting, Naive Bayes і Statistical Interval Classifier. У дослідженні використано базу даних Combined Measurement of ECG, Breathing, and Seismocardiograms, яка містить дані від 20 здорових людей. Розроблено метод побудови довірчих інтервалів для циклів ЕКГ, що базується на ритмо-адаптивній статистичній оцінці математичного сподівання та стандартного відхилення сигналу ЕКГ. Метод побудови довірчих інтервалів лежить в основі функціонування Statistical Interval Classifier у системі біометричної аутентифікації особи. Statistical Interval Classifier має найнижчу часову обчислювальну складність серед восьми досліджених класифікаторів, що виправдовує його використання в портативних системах біометричної аутентифікації, які мають незначні обчислювальні ресурси.*

Ключові слова: *біометрична аутентифікація, електрокардіограма, циклічно корельований випадковий процес, нормалізація сигналів, класифікація сигналів.*

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