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PRACTICAL APPLICATION OF IMPROVED SUPPORT VECTOR MACHINE ALGORITHM IN CARDIOVASCULAR DISEASE DIAGNOSTICS

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In the article, the problem of improving the support vector method based on the hybrid approach, designed to solve the problem of diagnosis of cardiovascular diseases in the medical field, is considered. It is noted that the hybrid approach in adjusting the hyperparameters of this method allows to achieve better results compared to individual methods.

The aim of the work is to develop an improved support vector machine based on an evolutionary hybrid algorithm by adjusting hyperparameters.

***Material and methods.** In this case, a hybrid algorithm was developed, which is a combination of particle swarm and artificial immune system algorithms, designed to adjust the hyperparameters of the support vector method.*

***Findings and their discussion.** This hybrid algorithm combines the global search capabilities of the particle swarm algorithm and the local optimization capabilities of artificial immune systems. In order to conduct experimental research using the developed algorithm, cardiovascular diseases in the medical field were selected. By perfectly adjusting the hyperparameters of the support vector method, the classification results were improved.*

***Conclusion.** Thus, the possibility of diagnosing several types of cardiovascular diseases with high accuracy was achieved. At the same time, results were obtained from the developed algorithm and existing algorithms, and they were compared and analyzed.*

***Key words:** particle swarm, hyperparameter, artificial immune system, hybrid algorithm, fitness value.*

ПРАКТИЧЕСКОЕ ПРИМЕНЕНИЕ УЛУЧШЕННОГО АЛГОРИТМА МАШИНЫ ОПОРНЫХ ВЕКТОРОВ В ДИАГНОСТИКЕ СЕРДЕЧНО-СОСУДИСТЫХ ЗАБОЛЕВАНИЙ

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В данной статье рассматривается проблема совершенствования метода опорных векторов посредством гибридного подхода, предназначенного для решения задачи диагностики сердечно-сосудистых заболеваний. Отмечается, что гибридный подход к настройке гиперпараметров этого метода позволяет добиться лучших результатов по сравнению с индивидуальными методами.

Цель исследования — разработать улучшенный метод опорных векторов на основе эволюционного гибридного алгоритма путем корректировки гиперпараметров.

***Материал и методы.** Авторами разработан гибридный алгоритм, представляющий собой комбинацию алгоритмов роя частиц и искусственного иммунитета, предназначенный для настройки гиперпараметров метода опорных векторов.*

Результаты и их обсуждение. *Предложенный гибридный алгоритм сочетает в себе возможности глобального поиска алгоритма роя частиц и возможности локальной оптимизации искусственного иммунитета. Для проведения экспериментальных исследований с использованием разработанного алгоритма были выбраны сердечно-сосудистые заболевания. Благодаря идеальной настройке гиперпараметров метода опорных векторов улучшены результаты классификации.*

Заключение. *Таким образом, достигнута возможность диагностики нескольких видов сердечно-сосудистых заболеваний с высокой точностью. При этом получены результаты, достигнутые с помощью разработанного алгоритма и существующих алгоритмов, а также проведены их сравнение и анализ.*

Ключевые слова: *рой частиц, гиперпараметр, искусственная иммунная система, гибридный алгоритм, показатель приспособленности.*

It is known that cardiovascular diseases (CVD) are among the most common diseases worldwide, and their complications can lead to serious negative consequences [1]. For this purpose, it is necessary to develop innovative methods that will be accurate and effective for early detection, prevention and treatment of these diseases [2; 3]. In this regard, automation and optimization of the medical diagnostics process using intelligent analysis methods, in particular support vectors and evolutionary algorithms, is one of the urgent issues. The article discusses the development of an improved support vector algorithm based on a hybrid approach for the diagnosis of several types of CVD.

Suppose that a set of weakly formed processes and objects (the research sample) is represented as follows: $x_{p1}, x_{p2}, \ldots, x_{pm_p} \in X_p, p = \overline{1,r}$. Here the object $x_{pi} = (x_{pi}^1,\ x_{pi}^2, \ldots x_{pi}^N), i = \overline{1, m_p}$ is considered in *an N*-dimensional data space, and $X_p, p = \overline{1,r}$ denotes a set of classes consisting of m_p objects $x_{p1}, \ldots, x_{p_{m_p}}$. At this time, it is necessary to determine to which class in a given training sample an object with an unknown class belongs $x^1{}_{m+t}, \ldots, x^n{}_{m+t}\ x_{m+t}^1, \ldots\ x_{m+t}^N$.

Purpose of the work: improve the support vector machine based on a hybrid approach designed to solve the problem of diagnosing cardiovascular diseases.

The aim of the work is to develop an improved support vector machine based on an evolutionary hybrid algorithm by adjusting hyperparameters.

Material and methods. Support Vector Machine (SVM) is widely used to analyze high-dimensional data in data mining problems. SVM is a data processing method that uses linear combinations of basis vectors to represent complex objects. One of the key aspects of working with SVM is the optimization of its hyperparameters, which improves the efficiency and quality of the model's predictions [4]. There are a number of parameter tuning methods, including gradient descent, genetic algorithms, particle swarm algorithms, artificial immune systems, and other widely used algorithms. A hybrid evolutionary approach to tuning the hyperparameters of an SVM model can achieve better results than individual methods [5; 6].

Below, we will consider the development of a hybrid algorithm formed by combining particle swarm optimization and artificial immune system algorithms for tuning SVM hyperparameters and its application to the problem of predicting SVM.

Brief description of the particle swarm algorithm. Particle swarm optimization (PSO) is an optimization algorithm that has been compared to the social behavior of birds and fish. The algorithm works by launching a swarm of particles into a motion space, where each particle represents a potential solution. The particles move through the search space toward the best position found by the swarm and toward their own best position, thereby approaching the optimal solution. It should be noted that the particle swarm algorithm is a popular evolutionary algorithm in the field of artificial intelligence and machine learning [7; 8].

In the particle swarm algorithm, particles (a swarm of agents) move through a search space in search of an optimal solution. Each particle in the swarm has three parameters: speed, position, and fitness value. Each particle keeps track of its best position. The global best position is the best value of any particle. Each particle in the swarm changes its direction depending on its current position, speed, and local and global best values [9; 10].

Brief description of the Artificial Immune System (AIS) algorithm. AIS is an adaptive computing system based on models, principles, mechanisms and functions described in theoretical immunology, used to solve practical problems.

Although natural immune systems have not been fully studied, today there are basic theories that explain the functioning of the immune system and describe the interaction of its elements, which are [11]:

• negative selection theory;
• clonal selection theory;
• immune network theory;

They served as the basis for the creation of four types of AIS algorithms (clonal selection algorithm, negative selection algorithm, immune network algorithm, dendritic algorithm) [12].

The main idea in creating the AIS algorithms was genetic and evolutionary computational algorithms. Both of these algorithms are evolutionary algorithms.

Below is information about AIS algorithms [13]:

1. Clonal selection algorithm. This type of AIS is based on the theory of clonal selection of the immune system. This involves creating a diverse set of antibodies and selecting the most effective ones through a process of clonal reproduction and mutation. This algorithm is often used to solve optimization, classification, and pattern recognition problems.
2. Negative selection algorithm: This algorithm is based on the immune system's concept of self-non-self differentiation. It involves creating a set of recognizable antibodies and comparing them with a set of other antigens to detect anomalies or deviations. The negative selection algorithm is commonly used to detect leaks and anomalies in computer networks.
3. Immune network algorithm: This algorithm is based on the interactions between immune cells of the immune system. It models the interactions as networks and uses network mechanisms such as immune network dynamics and immune network optimization to solve optimization and pattern recognition problems.
4. Dendritic cell algorithm: This algorithm is based on the behavior of dendritic cells of the immune system, which play an important role in antigen presentation and immune response. It involves collecting and processing information from antigens to generate appropriate responses. It is also used to solve various problems, including clustering and classification of data.

Almost all immune simulators are based on negative and clonal selection algorithms. Antigens are like bit strings — a sequence of zeros and ones. AIS must create antibody detectors that can quickly recognize anomalies in the data stream [14].

The algorithms of the AIS are used to find solutions to a number of complex mathematical and technological problems. Therefore, it can be considered one of the intelligent systems.

The above algorithms can be combined and used to tune the hyperparameters of the SVM algorithm. This provides increased diagnostic accuracy of the SVM classifier. The steps to implement an evolutionary hybrid algorithm designed to tune the hyperparameters of an SVM model for CVD prediction using particle swarm and artificial immune system algorithms are as follows:

1. Data input and standardization. Data about patients are read from the dataset used for CVD diagnosis and expressed as variables:

$$X = \left\{x_1,\ x_2,\ \ldots,\ x_n\right\},\ \ y = \left\{y_1,\ y_2,\ \ldots,\ y_n\right\}.$$

Then they are standardized:

$$X' = \frac{X - \mu}{\sigma},$$

where μ is the mean value, σ is the variance.

2. Optimization of SVM hyperparameters using particle swarm algorithm. The optimal parameters ***C*** and **γ** are determined using the particle swarm algorithm. The velocity of each particle is updated using the following formula:

$$v_i^{(t+1)} = wv_i^{(t)} + c_1 r_1 (p_i - x_i^{(t)}) + c_2 r_2 (g - x_i^{(t)}),$$

where *w* is the coefficient of inertia, c_1, c_2 is the velocity constant, r_1 , r_2 is a random number in the range [0,1], p_i — the best position of the particle, *g* — the global best position. The position of the particle is updated as follows:

$$x_i^{(t+1)} = x_i^{(t)} + v_i^{(t+1)} .$$

Fitness Function:

$$f(C,\gamma) = 1 - Accuracy(C,\gamma),$$

where *Accuracy (C ,γ)* — accuracy of the SVM model. Optimal *C* and *γ* are found as follows:

$$(C^*, \gamma^*) = \arg\min(C,\gamma).$$

3. Improve the identified hyperparameters using the artificial immune system algorithm. This algorithm further adapts *C* and *γ* through mutation:

$$C' = C \cdot (1 + \beta \cdot (r - 0.5)),$$
$$\gamma' = \gamma \cdot (1 + \beta \cdot (r - 0.5)),$$

where *β* — mutation rate (≈0.1), and *r* — a random number in the range [0,1]. The model with the best parameters is selected:

$$(C_{final}, \gamma_{final}) = \arg\min(C,\gamma).$$

4. Classification with a SVM model with tuned hyperparameters. The SVM model operates with the following radial basis function (RBF kernel):

$$K(x_i, x_j) = \exp(-\gamma \| x_i - x_j \|^2).$$

The SVM model performs classification using the following optimal hyperplane:

$$f(x) = \sum_{i=1}^{n} \alpha_i y_i K(x_i, x) + b \cdot$$

Here

$$f(x) \geq 0 \Rightarrow y = 1, \qquad f(x) < 0 \Rightarrow y = -1.$$

5. Iteration: Steps 2–4 are repeated until the specified iteration steps are completed or until high classification accuracy is achieved.

6. Predicting a new object. The new object X_{new} is standardized and fed to the SVM model:

$$\hat{y} = sign(\sum_{i=1}^{n} \alpha_i y_i K(x_i, X_{new}) + b).$$

7. End of the algorithm.

The goal of this hybrid algorithm is to create the best classifier by optimizing the hyperparameters of the SVM model, namely *C* and *γ*, using particle swarm and artificial immune system algorithms.

Results and their discussion. To test the developed algorithm, computational experiments were conducted on the CDD and ECG datasets used in the diagnosis of cardiovascular diseases (CVD). Datasets were obtained that predict the presence or absence of cardiovascular diseases (cardiovascular disease dataset, https://www.kaggle.com/datasets/jocelyndumlao/cardiovascular-disease-dataset) and diagnose cardiovascular diseases based on ECG data (ECG dataset, https://www.kaggle.com/code/thakursankalp/detecting-cardiac-ailments-ml-w-ecg-data). The CDD study sample included data from 1000 patients who had 12 features. The last column of the dataset is a class column indicating whether the disease is present (represented by 1) or absent (represented by 0).

ECG dataset consisted of 1200 records from patients diagnosed with CVD, which were divided into 4 groups according to the diagnoses given to the patients, namely: ARR — arrhythmia (1–300), AFF — fibrillation atrial (301–600), CHF — congestive heart failure (601–900), and NSR — normal sinus rhythm (901–1200). The data is based on the MIT-BIH physiological network database. So, the file contains records of 1200 x 56. Column 1 contains the serial number of the record, and column 56 contains the type of disease. The remaining columns are features, which are the results of the ECG [10].

These datasets are used to determine the diagnostic capabilities of the SVM algorithm and improved SVM algorithms based on the hybrid approach.

Below are the results obtained by the SVM algorithm using the CDD and ECG datasets (Fig. 1–2).

Results for the CDD dataset:

Classification report:

	precision	*recall*	*f1-score*	*support*
0	*0.96*	*0.95*	*0.96*	*83*
1	*0.97*	*0.97*	*0.97*	*117*
accuracy			*0.96*	*200*
macro avg	*0.96*	*0.96*	*0.96*	*200*
weighted avg	*0.96*	*0.96*	*0.96*	*200*

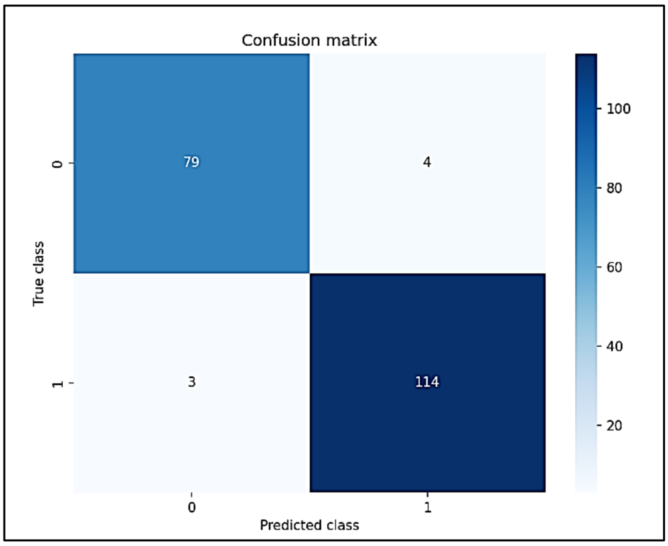

Fig. 1. **Confusion matrix obtained using the SVM algorithm on the CDD dataset**

Results for the ECG dataset:

Classification report:

	precision	*recall*	*f1-score*	*support*
AFF	*0.91*	*0.80*	*0.85*	*60*
ARR	*1.00*	*1.00*	*1.00*	*62*
CHF	*0.82*	*0.93*	*0.88*	*60*
NSR	*1.00*	*0.98*	*0.99*	*58*
accuracy			*0.93*	*240*
macro avg	*0.93*	*0.93*	*0.93*	*240*
weighted avg	*0.93*	*0.93*	*0.93*	*240*

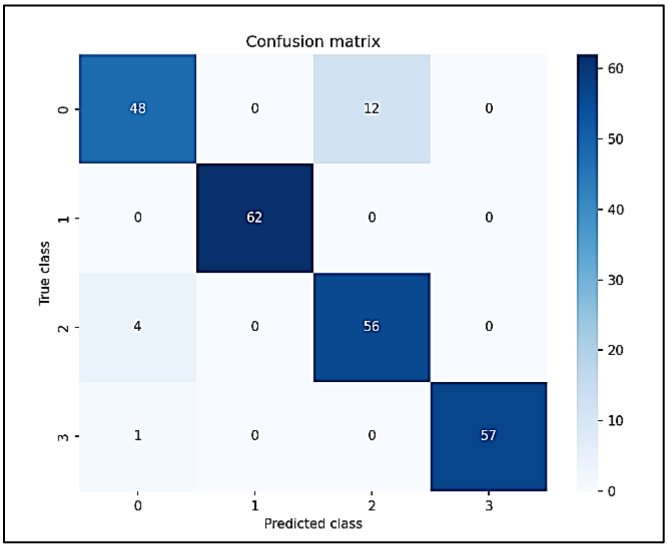

Fig. 2. **Confusion matrix obtained using the SVM algorithm on the ECG dataset**

The results obtained from the improved SVM algorithm based on the hybrid approach are presented below (Fig. 3–4).

Results for the CDD dataset:

Classification report:
precision recall f1-score support

0	*0.99*	*0.99*	*0.99*	*83*
1	*0.99*	*0.99*	*0.99*	*117*
accuracy			*0.99*	*200*
macro avg	*0.99*	*0.99*	*0.99*	*200*
weighted avg	*0.99*	*0.99*	*0.99*	*200*

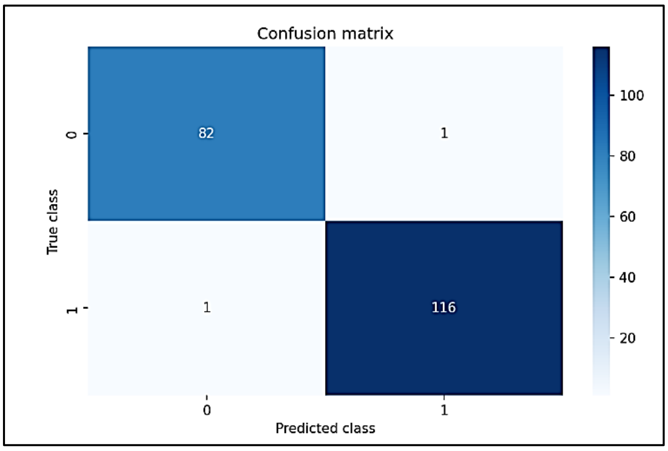

Fig. 3. **Confusion matrix obtained using the improved SVM algorithm on the CDD dataset**

Results for the ECG dataset:

Classification report:
precision recall f1-score support

AFF	*1.00*	*0.93*	*0.97*	*60*
ARR	*0.98*	*1.00*	*0.99*	*62*
CHF	*0.94*	*1.00*	*0.97*	*60*
NSR	*1.00*	*0.98*	*0.99*	*58*
accuracy			*0.98*	*240*
macro avg	*0.98*	*0.98*	*0.98*	*240*
weighted avg	*0.98*	*0.98*	*0.98*	*240*

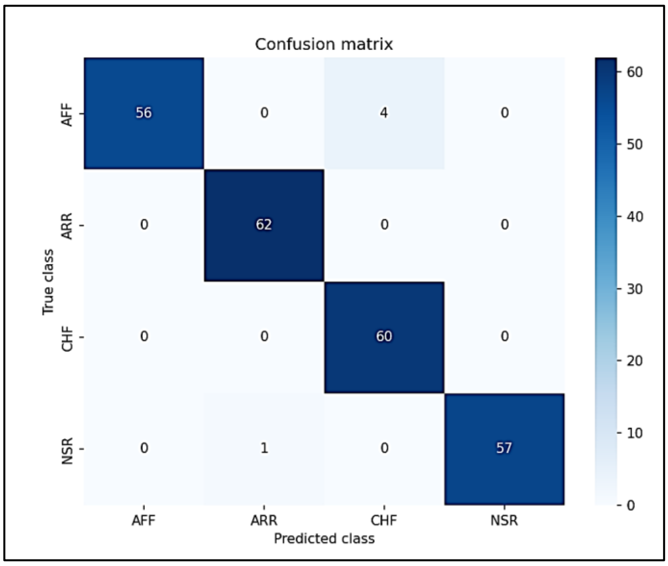

Fig. 4. **Confusion matrix obtained using the improved SVM algorithm on the ECG dataset**

The obtained results create the possibility of developing software tools with high diagnostic accuracy. The accuracy of the improved SVM algorithm is compared with the results obtained using existing classifiers in the WEKA and KNIME programs (Table).

Table

Classification accuracy of algorithms

	Naive Bayes	IBk	Random Forest	J48	S MO	Hybrid algorithm
In Weka	90.25%	97.33%	97.18%	97.28%	95.2%	98.0%
	Ada Boost	Logistic	Naive Bayes	SVM	Random Forest	Hybrid algorithm
In Knime	75.0%	93.33%	88.75%	93.75%	96.66%	98.0%

The table shows that the classification accuracy of the improved SVM algorithm is higher than that of other algorithms. This result was obtained by tuning the SVM hyperparameters using a combination of the PSO and AIS algorithms. The developed algorithm has the following advantages:

– Combines the global search capabilities of the particle swarm algorithm and the local optimization capabilities of artificial immune systems;
– The algorithm, developed using the mutation and selection mechanisms of the artificial immune system algorithm, increased its adaptability to various environments;
– The particle swarm algorithm approaches the optimal solution, while artificial immune systems improve it even more;
– Improving classification results by fine-tuning the hyperparameters of the SVM model.

Conclusion. The performance results of the proposed SVM algorithm itself and its improved version by adjusting the hyperparameters based on the evolutionary hybrid algorithm show that for the CDD dataset, the classification accuracy in the SVM algorithm was 96%, and in the improved algorithm — 99%. For the ECG dataset, the classification accuracy in the SVM algorithm was 93%, and in the improved algorithm — 98%. Accordingly, the accuracy was increased by 3% in the CDD dataset and by 5% in the ECG dataset by adjusting the hyperparameters. The application of the improved SVM algorithm to create software tools used to solve diagnostic problems significantly improves the diagnostic accuracy. Thus, it is possible to create a software tool with high diagnostic accuracy.

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