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NEURAL NETWORK MODEL OF HETEROASSOCIATIVE MEMORY FOR THE CLASSIFICATION TASK

The subject *of study in this article is the features of structural organization and functioning of the improved Hamming network as a model of neural network heteroassociative memory for classification by discriminant functions.* ***The goal*** *is to improve the neural network classifier based on the Hamming network, which implements the criterion of maximum similarity using discriminant functions and does not have restrictions on the representation of input data (not only binary data).* ***The tasks****: analyze the capabilities of associative memory models using neural networks as an example; analyze the features of classification on the principles of discriminant analysis; develop the structure of a neural network classifier as a model of neural network heteroassociative memory; perform simulation modeling of the classification process on the example of medical diagnosis.* ***The methods*** *used are a mathematical model of the functioning of a neural network as a classifier, and simulation in C#. The following* ***results*** *have been obtained: the structure of the neural network classifier has been improved through the formation connection matrix of a hidden layer from pre-calculated coefficients of linear discriminant functions, and the connection matrix of the output layer in the form symmetrical matrix with zeros on the main diagonal. This allows not only to simplify m connections, where m is the number of classes, in the structure of the output layer of the neural network classifier, but also to speed up the classification process, as well as to implement classification by the maximum of discriminant functions.* ***Conclusions****. The scientific novelty of the results obtained is as follows: the neural network classification method has been improved using pre-calculated elements of the connection matrices in the hidden and output layers of the classifier, which does not imply a long process of direct neural network learning with using discriminant functions; the structural organization of a neural network classifier is proposed, which is an improvement of the Hamming network as a model of heteroassociative memory, that allows using this classifier in a decision support system for medical diagnosis; the removal of positive feedback in neurons of the competitive (output) layer is implemented, which allows not only simplifies the structure of the neural network classifier but also speeds up the classification process almost 2 times, which is confirmed by the simulation results.*

Keywords: *heteroassociative memory; neural network classifier; classification; linear discriminant function.*

Introduction

In the classical neural network's theory [1, 2] the recurrent neural networks, which implement the functions of associative memory, take a worthy place [3, 4]. Illustrative examples of such neural networks are the Hopfield network, the Hamming network and the BAM network - Bidirectional Associative Memory [5, 6].

The main function of the neural network's associative memory is the determination of the pattern's mutual dependence and the reproduction of the corresponding pattern of those fixed in memory during the learning process [7, 8]. This article proposes a version of a neural network classifier, which is a further development of the Hamming network.

1. Work related analysis

The Hopfield network is an example of autoassociative memory since it can restore the nearest reference pattern from a distorted (noisy) pattern [3, 5]. For example, in neuroscience, the Hopfield network is used as a variant of the standard biologically plausible model of long-term memory [7].

The BAM network is a heteroassociative memory [2, 8], in which input objects (images) are associated with output ones. The publication [9] provides an example of the BAM network, which is improved using fuzzy sets.

The Hamming network is an example of a heteroassociative memory since it can choose a standard by its example (label), in this case by the minimum Hamming distance from the input pattern (vector) [2]. Thus, the Hamming network is an optimal classifier that implements the criterion for the classification by the minimum Hamming distance (Hamming metric) between binary vectors. On the basis of the Hamming network, various models and methods for learning classifiers were built to implement practical tasks [10, 11].

Due to this, the interest is the further development of a neural network approach for classifier construction, which implements the maximum likelihood method, but at the same time, there are no hard restrictions on the input data (not only binary data).

In terms of the specific implementation, it should be noted that network and neural network technologies are also used in such areas as associative processing (sorting) of numerical data [12, 13].

The goal is to improve the neural network classifier based on the Hamming network, which implements the criterion of maximum similarity using discriminant functions and does not have restrictions on the representation of input data (not only binary data).

The tasks to be solved: analyze the capabilities of associative memory models using neural networks as an example; analyze the features of classification on the principles of discriminant analysis; develop the structure of a neural network classifier as a model of neural network heteroassociative memory; perform simulation modeling of the classification process on the example of medical diagnosis.

2. Classification based on the principles of discriminant analysis

One of the promising applications of classifiers is medical diagnostics [14, 15] and biomedical research [16, 17] involving neural networks [18, 19] and neural technologies [20, 21]. At the same time, in medical diagnostics, the use of discriminant analysis provides good results in patients' diseases diagnosing [22, 23].

Thus, the comparative analysis of the diagnostic results of bronchopulmonary diseases is presented in the publication [24] and provided in two ways: a) as a model based on a multilayer perceptron; b) as a model based on the discriminant analysis.

The simulation results showed low reliability of the first model in some diagnostic cases. The second model showed good results - the diagnostic accuracy is more than 80 % [24]. Taking this into account, the second diagnostic model is preferable for the decision support system for diagnostic and specific disease treatment, since it is the corresponding statistical method that provides acceptable accuracy in logical reasoning [24].

Thus, the possibility of joint use of discriminant analysis as a statistical diagnostic method and a variant of the Hamming network as one of the fundamental approaches in neurotechnology provides interest.

In publication [17] a classification method using linear discriminant functions (LDF) was investigated taking into account the initial data with a limited statistical description. In this case, two levels of input data (features) processing should be distinguished. On the first level an LDFs group is formed in kind of:

$$g_i(X) = \sum_{j=1}^{n} w_{ij} \times x_j - b_i\,,\ i = \overline{1,m}\,, \qquad (1)$$

where x_j is the j-th element of the n-dimensional input vector X; w_{ij} – the weight of the j-th input of the i-th LDF element; b_i – classification threshold of the i-th LDF; m – number of classes.

The second level determines whether the input vector X belongs to the class C_k ($k = 1,\ldots,m$) according to the maximum of the k-th LDF $g_k(X)$. Thus, the following decision rule is implemented as:

$$X \in C_k \Leftrightarrow k = \underset{k=1,\ldots,m}{\operatorname{argmax}} \left\{ g_k(X) \right\}, \qquad (2)$$

where $C = \{C_1,\ldots,C_m\}$ is set of classes.

As one of the variants for implementing such an approach to classification by LDF, the two-layer neural network can be considered, the first (hidden) layer which (excluding the input layer) is a single-layer perceptron, and the second (output) layer is a detector of maximum, the function of which is effectively implemented by the MAXNET neural network [1, 2].

Thus, this classification method (1), (2) can be implemented using a two-layer neural network, the output layer of which implements the neuron competition mechanism according to the WTA ("Winner Takes All") or "1 from N" principle (Fig.1) [1, 2]. The main functional role in the classifier is played by such an output layer.

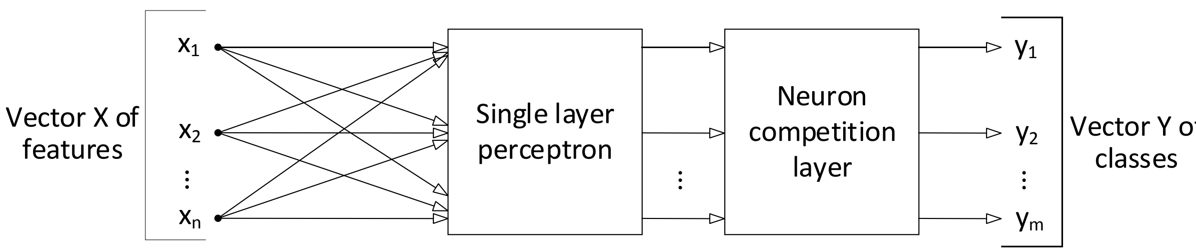

Figure 1. An example of a neural network classifier

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This structure of the proposed neural network classifier generally repeats the structure of the Hamming network. However, there are differences in functional properties between them, which are related to metric, compliance criteria, type of input data and areas of application.

3. The classifier as neural network model of heteroassociative memory

The structure of the proposed neural network classifier, which contains the input, hidden, and output layers of neurons [15] is shown in Fig. 2. In Fig. 2 the input vector X of the object`s features, the output vector Y of the object`s classes, the bias inputs of the neurons of the hidden layer displacement are shown.

The algorithm for the functioning of the neural network classifier consists of two functional stages.

The first stage in the functioning of the classifier is the initialization stage when the values of the weights w_{ij} (Fig. 2) of the matrix $\mathbf{W}^{(1)}$ for the neurons of the hidden layer are set. They are the corresponding LDF coefficients w_{ij} (1). In addition, the corresponding LDF classification thresholds b_i (1) are the set of the bias inputs of this layer neurons.

Thus, the classifier has all the features of a neural network with fixed connections, when the weight coefficients are formed based on the conditions of preliminary learning, and remain constant for this classification task, namely $dw / dt = 0$.

Therefore, such a neural network is an example of a neural network with a given weight matrix [1, 2]. This is associated with a combination of the statistical method of discriminant analysis with the peculiarity of the neural network classification of objects.

The weights $w_{ip}^{(2)}$ of the matrix $\mathbf{W}^{(2)}$ of lateral connections in the output layer neurons are also constant and formed during the initialization process as follows:

$$w_{ip}^{(2)} = \begin{cases} 0, \text{ if } i = p, \\ -\varepsilon \le \dfrac{1}{m}, \text{ if } i \ne p, \end{cases} \tag{3}$$

where ε is the value of the weights of lateral connections; $w_{ip}^{(2)}$ – the weight of the lateral connection between i-th and p-th neurons of the output layer, $i, p = 1,\ldots, m$.

From formula (3) it can be seen that weights of feedback are inhibitory, since they have a negative sign, and the output layer itself performs the functions of a competitive layer [1, 2].

The second stage is a performing stage, where the main functioning of neural network classifier takes place. With the receiving of the n-element input vector X of features, the corresponding LDF $g_i(X)$ of kind (1) is formed at the i-th neuron output of the hidden layer. In this case, the activation function of the hidden layer neurons can be represented as follows:

$$f^{(1)}(g_i(X)) = \max\{0, g_i(X)\} = \mathrm{ReLU}(g_i(X)), \tag{4}$$

where the function ReLU is a rectified linear unit.

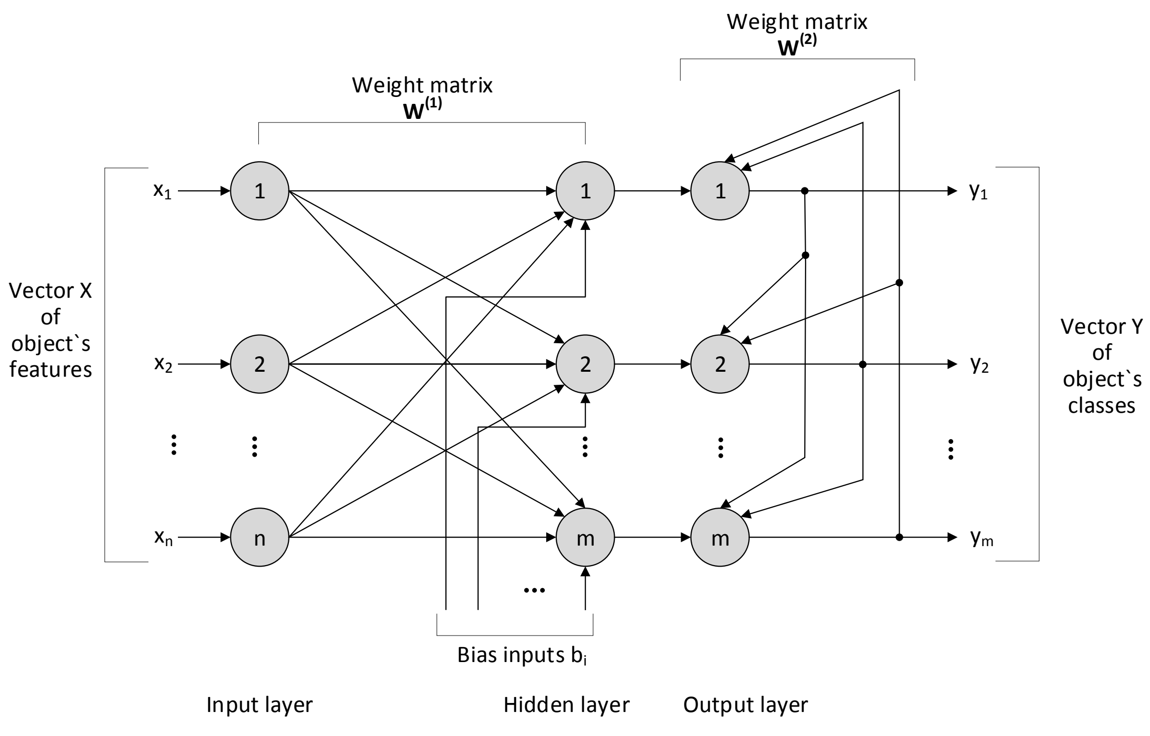

Figure 2. The structure of a neural network classifier

The obtained LDF values $g_i(X)$ specify the initial states of the corresponding neurons of the output layer, after that the iterative process inside this layer is started. The activation function at the neuron outputs of the output layer taking into account the change of value $y_i(t)$ in each iteration has the following form:

$$f^{(2)}(y_i(t)) = \max\{0, y_i(t)\} = \mathrm{ReLU}(y_i(t)) . \qquad (5)$$

This is due to the peculiarities of recurrent neural networks, in the competitive layer of which a fading iterative process occurs due to the presence of negative feedback (3). The iterative formula for the p-th neuron of this layer is:

$$y_p(t) = f^{(2)}(y_p(t-1) - \varepsilon \sum_{i=1}^{m} y_i(t-1)), i \neq p,\ p = 1,...,m, \quad (6)$$

where $y_p(t)$, $y_p(t-1)$ are the output signals of the p-th neuron of the output (competitive) layer at the t-th and (t-1)-th iterations, respectively.

As a result, the WTA strategy is implemented in the output layer through negative (inhibitory) connections between neurons. This stops the iterative process if one neuron wins, since the output signals $y_p(t)$ (6) fade to a level below the sensitivity threshold according to formula (5).

Thus, the convergence of the computational process is realized in the output layer of neural network classifier until the states of its neurons are stabilized, namely reaching the network attractor.

4. Features of the simulation of classification process

To carry out a simulation of the computational process in the proposed neural network classifier, a specific example of appendicitis disease diagnosis, given in [17], was chosen. The medical data were obtained on base by a description of 103 patients with proven cases of appendicitis disease of three types (y_1 – gangrenous, y_2 – phlegmonous, y_3 – catarrhal) and other abdominal pathology – y_4 [17].

At the same time, eight coded symptoms (x_1, ..., x_8) were declared, but one of them (x_5) turned out to be insignificant and was removed from consideration [17]. Examples of symptoms include pain in the right iliac region, pulse rate, white blood cells, Rovsing's symptom, protective muscle tension, and others.

The publication [15] contains the table of coded symptoms and a part of an information table from a learning data set. Using the software Statistica in [17] the matrix of weight coefficients w_{ij} and classification thresholds b_i for the hidden layer neurons were calculated. They are the corresponding coefficients and free elements of the LDF:

$$\begin{aligned} &\mathrm{LDF1} = -63{,}0 + 9{,}8x_1 + 3{,}6x_2 + 7{,}8x_3 + \\ &\quad + 5{,}2x_4 + 14{,}3x_6 + 11{,}8x_7 + 11{,}3x_8, \\ &\mathrm{LDF2} = -57{,}4 + 8{,}3x_1 + 4{,}9x_2 + 6{,}2x_3 + \\ &\quad + 4{,}3x_4 + 13{,}5x_6 + 11{,}7x_7 + 10{,}6x_8, \\ &\mathrm{LDF3} = -49{,}6 + 9{,}4x_1 + 4{,}7x_2 + 5{,}5x_3 + \\ &\quad + 3{,}0x_4 + 12{,}3x_6 + 12{,}0x_7 + 8{,}3x_8, \\ &\mathrm{LDF4} = -23{,}0 + 6{,}3x_1 + 2{,}5x_2 + 5{,}3x_3 + \\ &\quad + 2{,}8x_4 + 7{,}8x_6 + 7{,}0x_7 + 5{,}8x_8. \end{aligned} \qquad (7)$$

For comparative analysis of the computational process time characteristics of classification by LDF, two versions of this process were modeled: a) without positive feedback for each neuron of the output layer (3) (the proposed version); b) with the positive feedback's presence for each neuron of this layer (as in the Hamming network).

The simulation was performed in C#. During the modeling process, 15 examples were used for each of the four diagnoses in accordance with the table of medical data from the publication [17]. Fig. 3 shows an example of the results of calculation by formula (6) of LDF values (7) for specific symptom values (x_1, ..., x_8) [15, 17].

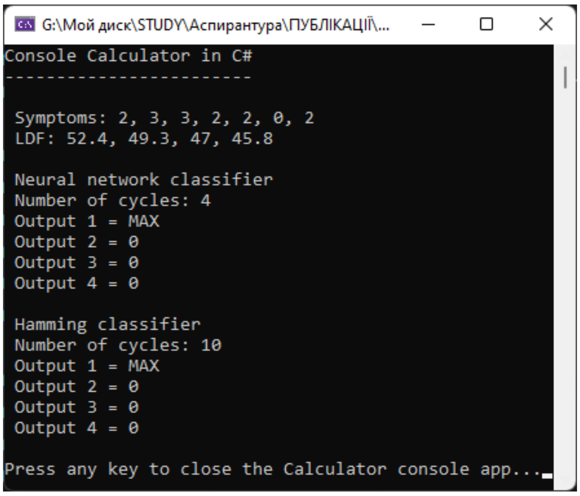

Figure 3. Results of simulation

This set of symptoms corresponds to the diagnosis of the disease y_1, which is indicated by the maximum value at the output of the first neuron of the output layer of the classifier in both simulation variants. The number of cycles is 4 and 10, respectively, for the neural network classifier and the Hamming network.

Table 1 presents examples for four variants of diagnosing the disease of appendicitis, indicating the

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number of cycles of the classification process for the neural network classifier and the Hamming network.

The results of this simulation confirmed the acceleration of the classification process by almost 2 times. This fact can be explained as follows. An increase in the difference between the output values (6) in all neurons of the output layer should accelerate the fading process.

At the same time, after each iteration in the Hamming network, the current output signal is doubled due to the presence of positive feedback ($w_{ii} = 1$) for each neuron of this layer.

As a result, in the second version of modeling the classification process is significantly slowed down, since it lasts until initial values are zeroed of all output layer neurons except for the winner-neuron. In addition, the simulation results showed the correct classification answers, which correspond to those given in [17].

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5. Results

Thus, the following changes to the structure of the neural network classifier have been made:

- the weight matrix $\mathbf{W}^{(1)}$ of the hidden layer consists of pre-calculated corresponding coefficients w_{ij} of LDFs, in contrast to those formed by the Hamming network;

- the weight matrix $\mathbf{W}^{(2)}$ of the output layer is a symmetric matrix with zeros on the main diagonal unlike a similar matrix with units on the main diagonal, which is typical for the Hamming network.

As a result, the transformation of matrix $\mathbf{W}^{(2)}$ not only simplifies the output layer structure of the neural network classifier by m connections but also speeds up the classification process.

This is confirmed by the simulation of the computational process in this layer. Both matrices are set during the initialization of the neural network classifier, which also distinguishes the proposed classifier from the Hamming network.

In addition, the neural network classifier performs analog signals processing, in contrast to the Hamming network, where binary signals are processed.

Comparative characteristics of the heteroassociative memory models as neural network classifiers are presented in table 2.

The disadvantage of the neural network classifier, like all neural networks, is the orientation towards a specific classification task.

Changing the classification task will lead to the recording of the hidden layer coefficients, as well as to a change in the number of neurons in both layers of the neural network classifier. At the same time, the connections in the layers (hidden and output) remains the same, respectively.

Conclusions

The proposed organization of the neural network classifier is a further development of the Hamming network is a model of heteroassociative memory with its classification capabilities.

The use of pre-calculated matrices of weight coefficients for the hidden and output layers in this version allows considering such a model as a neural network with fixed weights. This approach does not involve a lengthy learning process for the neural network.

Removing positive feedback from neurons of the competitive (output) layer allows not only simplifies the structure of the neural network classifier but also speeds up the classification process. The proposed approach to the neuron's weight initialization of classifier hidden layer as coefficients of discriminant functions makes it possible to expand the area of its application for classification according to the maximum of discriminant functions. This makes effective usage of the proposed neural network classifier possible in the decision support system for medical disease diagnosis.

Table 1

Results of simulation

Diagnosis options for appendicitis	**Set of coded symptoms**	**Maximum output value**	**The number of cycles**	
			Neural network classifier	**Hamming network**
Gangrenous y_1	2, 3, 3, 2, 2, 0, 2	Output 1 = MAX	4	10
Phlegmonous y_2	1, 4, 2, 2, 2, 2, 2	Output 2 = MAX	6	14
Catarrhal y_3	2, 1, 2, 2, 2, 2, 0	Output 3 = MAX	5	11
Other abdominal pathology y_4	1, 1, 2, 1, 0, 2, 0	Output 4 = MAX	2	3

Table 2

Characteristics of neural network models

Features of the neural network	Neural network classifier	Hamming network
Number of layers	Three layers (input, hidden, output)	Three layers (input, hidden, output)
The nature of the functioning	Relaxation upon reaching a stable state	Relaxation upon reaching a stable state
Metric	Discriminant function	Hamming distance
Compliance criteria	Maximum of discriminant function	Minimum Hamming distance
Method of learning	Pre-learning	Without learning
Kind of the weight matrix of the output layer	Symmetric matrix with zeros on the main diagonal	Symmetric matrix with units on the main diagonal
The presence of lateral connections	In the output layer (inhibitory connections)	In the output layer (inhibitory connections and positive feedback w_{ii})
The nature of the formation of weight connections	In hidden layer in setup process (fixed weight connections)	In hidden layer in setup process
Kind of activation function	ReLU – rectified linear unit (in hidden and output layers)	ReLU – rectified linear unit (in hidden and output layers)
Number of connections in the output layer	m(m-1)	m^2
Type of neuron structure	Homogeneity in the hidden and output layers, respectively	Homogeneity in the hidden and output layers, respectively
Type of input data	Digital	Binary
Method of synchronization	Synchronously in layers	Synchronously in layers
Areas of application	Classification of objects, medical diagnostics	Classification of objects, reliable signal transmission under interference conditions

A hardware implementation of the proposed structure of the neural network classifier based on an FPGA chip in the form of a special processor is planned.

Contributions of authors: development of conceptual provisions and methodology of research – **T. Martyniuk**; selection and application of software tools, analysis of research results and presentation of results – **B. Krukivskyi**; development of mathematical models and formulation of the purpose and tasks of research – **L. Kupershtein**; analysis of references and formulation of conclusions – **V. Lukichov**. All authors have read and agreed to the published version of the manuscript.

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МОДЕЛЬ НЕЙРОМЕРЕЖЕВОЇ ГЕТЕРОАСОЦІАТИВНОЇ ПАМ’ЯТІ ДЛЯ ЗАДАЧІ КЛАСИФІКАЦІЇ

Т. Б. Мартинюк, Б. І. Круківський, Л. М. Куперштейн, В. В. Лукічов

Предметом вивчення в статті є особливості структурної організації та функціонування вдосконаленої мережі Хеммінга як моделі нейромережевої гетероасоціативної пам’яті для задачі класифікації за дискримінантними функціями. **Метою** є удосконалення нейромережевого класифікатора на базі мережі Хеммінга, в якому реалізується критерій максимальної подібності з використанням дискримінантних функцій та відсутні обмеження на подання початкових даних (не тільки бінарні дані). **Завдання**: проаналізувати можливості моделей асоціативної пам’яті на прикладі нейромереж; проаналізувати особливості класифікації на принципах дискримінантного аналізу; розробити структуру нейромережевого класифікатора як моделі нейромережевої гетероасоціативної пам’яті; виконати імітаційне моделювання процесу класифікації на прикладі медичного діагностування. Використовуваними **методами** є математична модель функціонування нейромережі як класифікатора, імітаційне моделювання на мові C#. Отримано такі **результати**: вдосконалено структуру нейромережевого класифікатора через утворення матриці зв’язків прихованого шару з попередньо розрахованих коефіцієнтів лінійних дискримінантних функцій, а матриці зв’язків вихідного шару – у вигляді симетричної матриці з нульовими елементами на головній діагоналі. Це дозволяє не тільки спростити на m зв’язків, де m – кількість класів, структуру вихідного шару нейромережевого класифікатора, але й прискорити процес класифікації, а також реалізувати класифікацію за максимумом дискримінантних функцій. **Висновки**. Наукова новизна отриманих результатів полягає в наступному: вдосконалено метод нейромережевої класифікації з використанням попередньо розрахованих елементів матриць зв’язків у прихованому та вихідному шарах класифікатора, що не передбачає тривалого процесу безпосереднього нейромережевого навчання з використанням дискримінантних функцій; запропоновано структурну організацію нейромережевого класифікатора, яка є удосконаленням мережі Хеммінга як моделі гетероасоціативної пам’яті, що дозволяє застосувати цей класифікатор у системі підтримки прийняття рішень при медичному діагностуванні; реалізовано видалення додатних зворотних зв’язків у нейронів конкурентного (вихідного) шару, що дозволяє не тільки спростити структуру нейромережевого класифікатора, але й прискорити процес класифікації майже у 2 рази, що підтверджено результатами імітаційного моделювання.

Ключові слова: гетероасоціативна пам'ять; нейромережевий класифікатор; класифікація; лінійна дискримінанта функція.

МОДЕЛЬ НЕЙРОСЕТЕВОЙ ГЕТЕРОАССОЦИАТИВНОЙ ПАМЯТИ ДЛЯ ЗАДАЧИ КЛАССИФИКАЦИИ

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Предметом изучения в статье являются особенности структурной организации и функционирования усовершенствованной сети Хэмминга как модели нейросетевой гетероассоциативной памяти для задачи классификации по дискриминантным функциям. **Целью** является усовершенствование нейросетевого классификатора на базе сети Хэмминга, в котором реализуется критерий максимального сходства с использованием дискриминантных функций и отсутствуют ограничения на представление входных данных (не только бинарные данные). **Задачи**: проанализировать возможности моделей ассоциативной памяти на примере нейросетей; проанализировать особенности классификации на принципах дискриминантного анализа; разработать структуру нейросетевого классификатора как модели нейросетевой гетероассоциативной памяти; выполнить имитационное моделирование процесса классификации на примере медицинского диагностирования. Используемыми **методами** являются математическая модель функционирования нейросети как классификатора, имитационное моделирование на языке C#. Получены следующие **результаты**: усовершенствована структура нейросетевого классификатора в результате построения матрицы связей скрытого слоя на основе предварительно рассчитанных коэффициентов линейных дискриминантных функций, а матрицы связей выходного слоя – в виде симметричной матрицы с нулевыми элементами на главной диагонали. Это позволяет не только упростить на m связей, где m – количество классов, структуру выходного слоя нейросетевого классификатора, но и ускорить процесс классификации, а также реализовать классификацию по максимуму дискриминантных функций. **Выводы**. Научная новизна полученных результатов заключается в следующем: усовершенствован метод нейросетевой классификации с использованием предварительно рассчитанных элементов матриц связей в скрытом и выходном слоях классификатора, что не предполагает длительного процесса непосредственного нейросетевого обучения с использованием дискриминантных функций; предложена структурная организация нейросетевого классификатора, которая является усовершенствованием сети Хэмминга как модели гетероассоциативной памяти, позволяющей использовать этот классификатор в системе поддержки принятия решений при медицинском диагностировании; реализовано удаление положительных обратных связей у нейронов конкурентного (выходного) слоя, что позволяет не только упростить структуру нейросетевого классификатора, но и ускорить процесс классификации почти в 2 раза, что подтверждено результатами имитационного моделирования.

Ключевые слова: гетероассоциативная память; нейросетевой классификатор; классификация; линейная дискриминантная функция.

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