Intelligent Support for Medical Decision Making

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Abstract. This paper presents the development and study of a model for formalizing the process of making a diagnosis using artificial intelligence methods. Currently, various artificial neural networks and expert systems have been created and are used for diagnosis. Analysis of these works has shown that these methods show good results, but have a number of drawbacks, the most significant of which is the complexity of organization and the significant time required to train a neural network. Thus, the problem is to develop new algorithms that have a probability of making an accurate diagnosis, comparable with artificial neural networks and expert systems, while having a shorter training time. One of the ways to solve this problem is to develop a model for diabetes diagnosis based on an artificial immune system. The purpose of this work is to develop and study of a model for formalizing the process of diagnosis using methods of artificial intelligence. The paper reviews a model of the diagnosis process: pre-diabetes (impaired glucose tolerance, impaired fasting glycemia), type I diabetes, type II diabetes. The problem of diagnosing the disease can be regarded as a classification problem. In this paper, the process of diagnosis was examined as a division of test data and patient history into four classes corresponding to one of the diagnoses: pre-diabetes (impaired glucose tolerance, impaired fasting glycemia), type I diabetes, type II diabetes. An artificial immune system and Kohonen artificial neural network were used to solve this problem.

Keywords: Diabetes mellitus · Artificial neural network · Artificial immune system

1 Introduction

At presentation a diagnosis, the medical practitioner has to process a large amount of information. This increases the physician's information load, which leads to physical and psychological fatigue, errors in selecting and administering treatment, or delaying the process of making an accurate diagnosis. Therefore, it is clear that there is currently a trend toward increasing the number of diagnostic medical information systems (MIS) being developed. In addition, Government Decree No. 555 of May 05, 2018 "On the Unified State Health Information System" promotes the growth of health information system implementations.

MIS helps medical workers, facilitates their work, and improves the quality of medical services [1–7].

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This paper discusses algorithms that allow for differential diagnosis of type I and type II diabetes mellitus, impaired glucose tolerance, and fasting glycemia disorders.

The optimal treatment regimens for patients with diabetes mellitus (DM) have become an increasingly urgent task over the years. In spite of the efforts of health care organizations in many countries, the number of people with diabetes is steadily increasing. The disease is the fourth leading cause of premature death in the world. Today it affects about 422 million people, which is 6.028% of the world's population. In Russia about 8 million people suffer from diabetes. Over the last decades, physicians have recorded a steady increase in the incidence of diabetes in all age groups. In the past the disease was more widespread among the people older than 40 years old, today even children and teenagers suffer from it. Researches show that each age group is specific in its own way about the course of the disease. The causes of the disease are not fully investigated. However, scientists believe that the main source of this trend is a sedentary lifestyle and a negative environmental situation.

There are a number of domestic and foreign studies that tried to diagnose type I or type II diabetes mellitus, and they used artificial intelligence technologies as their basis. Among them are the works of E.A. Pustozerov, T.A. Obelets, Kiran Tangod, O.P. Shesternikova, Dilip Kumar Chubi, O.M. Alade, J. Vijayashri, J. Jayashri [8–15].

The analysis of these works has shown that these methods show good results, but have a number of drawbacks, the most significant of which is the complexity of organization and the long time required to train a neural network. Therefore, the problem is to develop new algorithms that have a probability of making an accurate diagnosis, comparable with artificial neural networks and expert systems, while having a shorter training time. One of the ways to solve this problem is to develop a model of diabetes diagnosis based on an artificial immune system.

1.1 Objective of the Work

The objective of this work is to develop and investigate a model for formalizing the process of diagnosis using artificial intelligence methods.

1.2 Materials and Methods

Let's consider a model of the diagnosis process: pre-diabetes (impaired glucose tolerance, impaired fasting glycemia), type I diabetes, type II diabetes.

The problem of diagnosing the disease can be regarded as a classification problem. In this work, the process of diagnosis was considered as a division of test data and patient history into four classes, corresponding to one of the diagnoses: pre-diabetes (impaired glucose tolerance, impaired fasting glycemia), type I diabetes, type II diabetes.

An artificial immune system and Kohonen artificial neural network were used to solve this problem.

Artificial immune system represents an idealized version of its natural counterpart and reproduces the key components of the natural process: selection of the best antibodies of the population depending on their affinity to the antigen, cloning of antibodies, mutation of antibodies [16–23, 24].

In the proposed artificial immune system, a vector g, is considered as an antigen, which components are real and Boolean values reflecting the data obtained during the collection of anamnesis and clinical examinations of the patient whose diagnosis needs to be determined. $g = (g_1, g_2 \ldots g_{15})$, where g_1 is the patient's gender, g_2 is a Boolean variable reflecting the fact that the patient had a child over 4 kg, g_3 – is age, g_4 – is weight, g_5 – is height, g_6 – is body mass index, g_7–g_9 are Boolean variables reflecting whether the patient had relatives with diabetes, polydipsia and polyuria, g_{10} – is fasting plasma glucose level, g_{11} – is plasma glucose level 2 h after use of oral glucose tolerance test, g_{12} – is glucose level at random determination, g_{13} – HbA1c, g_{14} – is insulin, g_{15} – C - peptide.

The antibody is a vector, $l = (l_1, l_2 \ldots l_{16})$, where l_1–l_{15} is a sequence of real and Boolean values similar to the antigen, l_{16} – is the patient's diagnosis that corresponds to such indicators. The components of antibody and antigen vectors we will call genes. Antibodies belong to one of four classes, according to the diagnosis: type 1 or type 2 diabetes, impaired glucose tolerance, impaired fasting glycemia. The task of the immune system is to determine which class the antigen belongs to.

The learning algorithm of the artificial immune system can be represented as follows.

1. The user enters the name of the diagnosis to be taught to the system in the text field and initiates training.
2. A group of antibodies $l_i, i = 1 \ldots n$, is created, each of which receives the name of the diagnosis entered by the user. The values of the vector components of each antibody are set randomly.
3. An antigen $g = (g_1, g_2 \ldots g_{15})$ is randomly selected from the training dataset, with values corresponding to the diagnosis entered by the user.
4. The antibody-antigen affinity function is calculated according to the following rule:
5. $A = k/15$, where k – is the number of antibody genes x_i, satisfying the condition
6. $|l_i - g_i| \leq \alpha, i = 1, \ldots, 15, \alpha = 0,05$.
7. For t antibodies with affinity to the antigen exceeding the set threshold p, a cloning procedure is applied, in which m copies of each antibody are created.
8. A mutation operator is applied to antibody clones, consisting of randomly selecting genes and making random changes in their values.
9. The affinity of antibody clones is calculated.
10. Destroying l ($l > mt$) antibodies with the lowest affinity.
11. Population number is restored by generating randomly $n - l$ new antibodies.
12. Steps 4–9 are repeated until the population stabilizes over a number of cycles.
13. Steps 3–9 are repeated until all antigens from the training sample have been used.
14. All antibodies from the population are added to a separate group to be used for further diagnosis.

The described process is repeated if the immune system needs to be trained for other diagnoses.

The diagnosis is obtained on the basis of the following sequence of steps:

1. A vector containing the data of the patient to be diagnosed is presented to the system as an antigen.

2. A number of antibodies belonging to different classes of possible diagnoses are randomly selected from the population of antibodies.
3. The number of antibodies in the selected population belonging to class d_i^1 is counted, where $i = 1,\ldots,4$.
4. Steps 4–10 of the previous algorithm are repeated for the selected population until its stabilization for a certain number of cycles is achieved.
5. The number of antibodies in the selected population belonging to the class number id_i^2 where $i = 1,\ldots,4$ is selected.
6. For each class we calculate the rati $v_i = \frac{d_i^2}{d_i^1}, i = 1, \ldots 4$.

If only one of these relations is greater than 1, the class number corresponds to the diagnosis; otherwise, steps 2–6 are repeated, but only antibodies of classes for which $v_i > 1$ are included in the population.

The diagnosis problem can be considered as a classification problem. The classification problem was solved using the Kohonen neural network.

In the Kohonen network the number of inputs of each neuron is equal to the dimensionality of parameters of the classified object. In our case, we will classify the results of analysis and patient data. As defined earlier, patient data contains 15 parameters, i.e. each neuron has fifteen inputs. The number of neurons is equal to the number of diagnoses that can be given to patients. In this paper, the patients will be divided into four groups:

1. patients with type I diabetes mellitus;
2. patients with type II diabetes mellitus;
3. patients with impaired fasting glycemia;
4. patients with impaired glucose tolerance.
5. The training algorithm for the Kohonen network consists of the following steps.
6. Network Initialization.
7. Assigning small random values to the weights of the network $W_{ij}, i = \overline{1,n}, j = \overline{1,m}$. The following values are set: α_0 – the initial learning rate and D_0 – the maximum distance between the weight vectors (columns of the matrix W).
8. Presenting the network with a new input signal X from the training sample.
9. Calculating the distance from input X to all neurons of the network:
10. $d_j = \sum_{i=1}^{n} \left(X_i - W_{ij}^N\right)^2, j = \overline{1,m}$
11. Selection of the neuron $k, 1 \le k \le m$ with the shortest distance d_k from the input to the network neurons.
12. Adjustment of weights of the k-th neuron and all neurons that are at a distance not exceeding D_N : $W_{ij}^{N+1} = W_{ij}^N + \alpha_N\left(X_i - W_{ij}^N\right)$.
13. Decreasing values of α_N, D_N.

Steps 2–7 are repeated until the weights stop changing (or until the total change of all weights is less than the value set by the user).

After the network is trained, the diagnosis is made by feeding the test vector to the network input and calculating the distance from it to each neuron, followed by selecting

the neuron with the shortest distance as the class indicator. The number of the selected class corresponds to the diagnosis of the patient.

1.3 Results

The accuracy of diagnosis using an artificial neural network and an artificial immune system was compared.

Data from 186 patients with known final diagnoses were used to organize the software package. The training sample included 100 records, the control sample included 86 records.

Patients' diagnoses that were obtained during the work of the program complex were compared with the known final diagnoses, and then the percentage of coincidence with those obtained during the work of the program was calculated (Table 1).

Table 1. Comparison of diagnosis results

Method	Percentage of correct diagnoses
Linear classifier (neural network with 1 layer)	88%
Kohonen neural network	92%
Artificial immune system with initial population n = 80	95%
Artificial immune system with initial antibody population n = 100	96%
Artificial immune system with initial antibody population n = 200	96%

As can be seen from the results of the experiments, the best results were shown by the artificial immune system with an initial population of more than 100 antibodies.

A software package that implements the developed algorithms and models **was developed**. The development environment C++ Builder and Paradox DBMS were chosen to implement the tasks. The functional diagram of the software product is shown in Fig. 1.

The software package is divided into 2 parts, the user (patient) part and the administrator (doctor) part. The first part of the system is for the work of the administrator (doctor), it is designed to accumulate and store information, set up training and making a diagnosis using the artificial neural network and artificial immune system. The second part provides the user's (patient's) work and is intended for making a diagnosis. The structural diagram of interaction between the main modules is shown in Fig. 2.

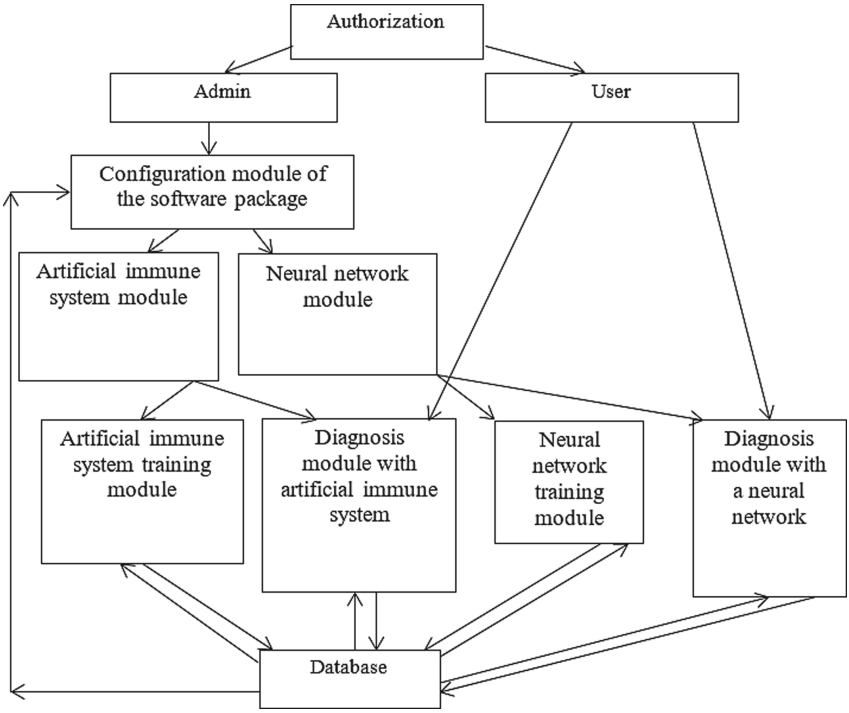

Fig. 1. Functional diagram of the software package.

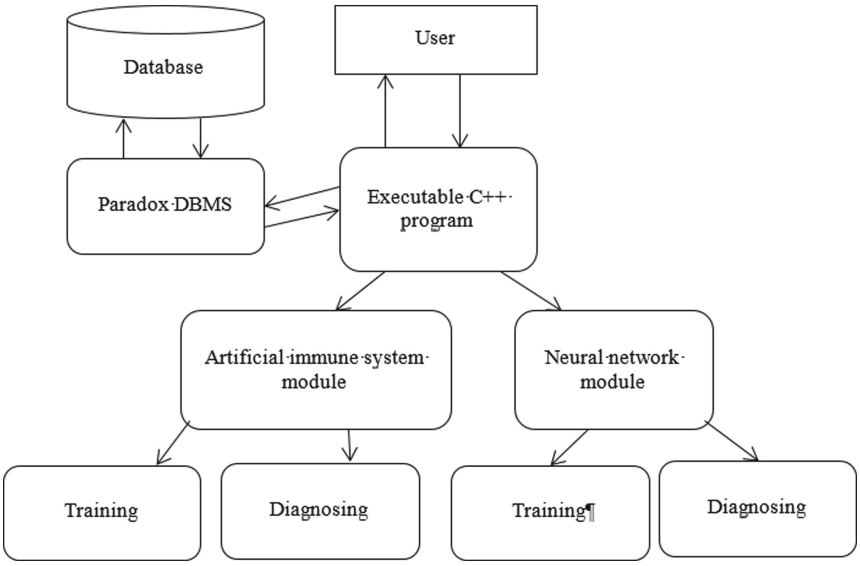

Fig. 2. Block diagram of the interaction between the modules of the software package.

1.4 Summary

The following main results are obtained in this paper.

- A formal model of the diagnosis process was developed.
- Diagnosis algorithm was developed: prediabetes (impaired glucose tolerance, impaired fasting glycemia), type I diabetes, type II diabetes, distinguished by the use of artificial immune system.
- The algorithm and model of Kohonen neural network, allowing to solve the problem of prediabetes state (disorder of glucose tolerance, disorder of fasting glycemia), type I diabetes, type II diabetes were developed.
- Comparison of the effectiveness of diagnosis using neural networks and artificial immune system was made.
- A software package implementing the described algorithms was created.

References

1. Haglin, J.M., Jimenez, G., Eltorai, A.E.M.: Artificial neural networks in medicine. Health Technol. **9**(1), 1–6 (2018). https://doi.org/10.1007/s12553-018-0244-4
2. Soumya, C.V., Ahmed, M.: Artificial neural network based identification and classification of images of Bharatanatya gestures. In: Innovative Mechanisms for Industry Applications, pp. 162–166 (2017)
3. Nowikiewicz, T., Wnuk, P., Małkowski, B., Kurylcio, A., Kowalewski, J., Zegarski, W.: Application of artificial neural networks for predicting presence of non-sentinel lymph node metastases in breast cancer patients with positive sentinel lymph node biopsies. Arch. Med. Sci. **13**(6), 1399–1407 (2017)
4. Sheikhtaheri, A., Sadoughi, F., Hashemi Dehaghi, Z.: Developing and using expert systems and neural networks in medicine: a review on benefits and challenges. J. Med. Syst. **38** (2014). Article number: 110. https://doi.org/10.1007/s10916-014-0110-5
5. Ultsch, A., Korus, D., Kleine, T.O.: Integration of neural networks and knowledge-based systems in medicine. In: Barahona, P., Stefanelli, M., Wyatt, J. (eds.) AIME 1995. LNCS, vol. 934, pp. 425–426. Springer, Heidelberg (1995). https://doi.org/10.1007/3-540-60025-6_170
6. Summers, R.M.: Deep learning and computer-aided diagnosis for medical image processing: a personal perspective. In: Lu, L., Zheng, Y., Carneiro, G., Yang, L. (eds.) Deep Learning and Convolutional Neural Networks for Medical Image Computing. ACVPR, pp. 3–10. Springer, Cham (2017). https://doi.org/10.1007/978-3-319-42999-1_1
7. Wang, J., Shi, M., Zheng, P., Xue, S., Peng, R.: Quantitative analysis of Ca, Mg, and K in the roots of Angelica pubescens f. biserrata by Laser-induced breakdown spectroscopy combined with artificial neural networks. J. Appl. Spectrosc. **85**(1), 190–196 (2018). https://doi.org/10.1007/s10812-018-0631-7
8. Sejdinović, D., et al.: Classification of prediabetes and type 2 diabetes using artificial neural network. In: Badnjevic, A. (ed.) CMBEBIH 2017, vol. 62, pp. 685–689. Springer, Singapore (2017). https://doi.org/10.1007/978-981-10-4166-2_103
9. Alade, O.M., Sowunmi, O.Y., Misra, S., Maskeliūnas, R., Damaševičius, R.: A neural network based expert system for the diagnosis of diabetes mellitus. In: Antipova, T., Rocha, Á. (eds.) MOSITS 2017. AISC, vol. 724, pp. 14–22. Springer, Cham (2018). https://doi.org/10.1007/978-3-319-74980-8_2

10. Srivastava, S., Sharma, L., Sharma, V., Kumar, A., Darbari, H.: Prediction of diabetes using artificial neural network approach. In: Ray, K., Sharan, S.N., Rawat, S., Jain, S.K., Srivastava, S., Bandyopadhyay, A. (eds.) Engineering Vibration, Communication and Information Processing. LNEE, vol. 478, pp. 679–687. Springer, Singapore (2019). https://doi.org/10.1007/978-981-13-1642-5_59
11. Li, X.: Artificial intelligence neural network based on intelligent diagnosis. J. Ambient. Intell. Humaniz. Comput. **12**(1), 923–931 (2020). https://doi.org/10.1007/s12652-020-02108-6
12. Asad, M., Qamar, U.: A review of continuous blood glucose monitoring and prediction of blood glucose level for diabetes type 1 patient in different prediction horizons (PH) using artificial neural network (ANN). In: Bi, Y., Bhatia, R., Kapoor, S. (eds.) IntelliSys 2019. AISC, vol. 1038, pp. 684–695. Springer, Cham (2020). https://doi.org/10.1007/978-3-030-29513-4_51
13. Raihan, M., Alvi, N., Tanvir Islam, M., Farzana, F., Mahadi Hassan, M.: Diabetes mellitus risk prediction using artificial neural network. In: Uddin, M.S., Bansal, J.C. (eds.) IJCCI 2019. AIS, pp. 85–97. Springer, Singapore (2020). https://doi.org/10.1007/978-981-15-3607-6_7
14. Arul Kumar, D., Jayanthy, T.: Application of back propagation artificial neural network in detection and analysis of diabetes mellitus. J. Ambient. Intell. Humaniz. Comput. **12**(7), 7063–7070 (2020). https://doi.org/10.1007/s12652-020-02371-7
15. Jayashree, J., Kumar, S.A.: Linear discriminant analysis based genetic algorithm with generalized regression neural network – a hybrid expert system for diagnosis of diabetes. Program. Comput. Softw. **44**, 417–427 (2018). https://doi.org/10.1134/S0361768818060063
16. Şahan, S., Polat, K., Kodaz, H., Güneş, S.: The medical applications of attribute weighted artificial immune system (AWAIS): diagnosis of heart and diabetes diseases. In: Jacob, C., Pilat, M.L., Bentley, P.J., Timmis, J.I. (eds.) ICARIS 2005. LNCS, vol. 3627, pp. 456–468. Springer, Heidelberg (2005). https://doi.org/10.1007/11536444_35
17. Lin, H., Su, C., Wang, P.: An application of artificial immune recognition system for prediction of diabetes following gestational diabetes. J. Med. Syst. **35**, 283–289 (2011). https://doi.org/10.1007/s10916-009-9364-8p283-289
18. Chikh, M.A., Saidi, M., Settouti, N.: Diagnosis of diabetes diseases using an Artificial Immune Recognition System2 (AIRS2) with fuzzy K-nearest neighbor. J. Med. Syst **36**, 2721–2729 (2012). https://doi.org/10.1007/s10916-011-9748-4
19. Wu, J.-Y.: Hybrid artificial immune algorithm and CMAC neural network classifier for supporting business and medical decision making. In: Tang, J., King, I., Chen, L., Wang, J. (eds.) ADMA 2011. LNCS (LNAI), vol. 7121, pp. 41–54. Springer, Heidelberg (2011). https://doi.org/10.1007/978-3-642-25856-5_4
20. Xiaoyang, F., Zhang, S.: An improved artificial immune recognition system based on the average scatter matrix trace criterion. In: Tan, Y., Shi, Y., Ji, Z. (eds.) Advances in Swarm Intelligence, pp. 284–290. Springer Berlin Heidelberg, Berlin, Heidelberg (2012). https://doi.org/10.1007/978-3-642-30976-2_34
21. Astachova, I.F.: The application of artificial immune system for parallel process of calculation and their comparison with existing methods. In: Journal of Physics: Conference Series, vol. 1202, p. 012003 (2019). https://doi.org/10.1088/1742-6596/1202/1/012003
22. Kashirina, I.L.: Neural network technologies. VGU, Voronezh (2008)
23. Astahova, I.F., Kiseleva, E.I.: Algorithm for using an artificial immune system to optimize the target component of the educational information system. Voronezh State University Bulletin. System Analysis and Information Technology **2**, 61–65 (2017)