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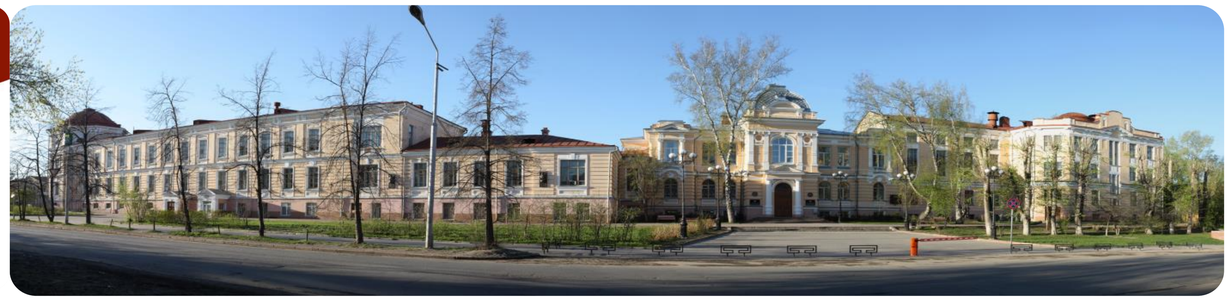
# Creating a neural network model based on glycemic variability indices to predict the degree of compensation for type 1 diabetes



## Actuality

***Many studies have shown that poor glucose control is one of the risk factors directly related to microvascular complications in type 1 diabetes and mortality in type 1 diabetes.***

***Nowadays HbA1c has become the target standard for measuring the level of total glycemic control and assessing the risk of diabetes complications, determining the choice of therapeutic tactics by a doctor, but it displays only the average glycemic level and does not allow the assessment of fluctuations over different periods of time.***

***CGMS is make it possible to identify certain tendencies of fluctuations in glycemia - glycemic variability, with registration of all episodes of hypo- and hyperglycemia, to find out the causes of their occurrence, which cannot be estimated when determining glycemia using a glucometer.***

***At present, close attention is paid in diabetology to glycemic variability indices, and a number of studies prove the relationship of these indices with the level of control and compensation of diabetes mellitus.***

***Since the standard methods of assessing the level of control and compensation of diabetes are not always accurate, it is the analysis of blood glucose variability indices will enable the practitioner to make a true and correct decision regarding the tactics of treatment of a patient with diabetes to achieve compensation of disease.***

## Objective

**To conduct a comparative analysis of glycated hemoglobin (HbA1c) and glycemic variability indexes to predict the degree of compensation for the diabetes mellitus type 1**

## Materials and methods

**The study included 80 patients with type 1 diabetes mellitus, aged 8-18 years (12.6 ± 2.8), receiving insulin therapy in a pump mode with the possibility of continuous monitoring of glycemia. 70 patients were randomly selected for inclusion in the training sample, 10 patients made up a test one.**

**The subjects transmitted data on self-monitoring, insulin therapy and diet to the doctor using various programs for continuous monitoring of glycemia. All patients underwent glycated hemoglobin (HbA1c) analysis.**

## Materials and methods

**As independent parameters for predicting the level of HbA1c, glycemic variability indices calculated using the EasyGV calculator were chosen:**

- **SD - standard deviation, mmol/l**
- **MAGE - average amplitude of vibrations, mmol/l**
- **CONGA - index of long-term increase in glycemia, mmol/l**
- **J-index - quality control index**
- **LI - lability index, predictor of hypoglycemia**
- **LBGI - Hypoglycemia risk index**
- **HBGI - Hyperglycemia risk index**
- **ADRR - medium risk index**
- **Mvalue - quality control, mmol/l**
- **MAG - glycemic change rate, mmol/l/hour**

**The regression neural network model was built in the type R statistical computing environment using the Neuralnet. The structure of the model was chosen by comparing more than 20 thousand test models. Statistical analysis was performed using the SPSS 23.0 software (IBM SPSS Statistics, USA).**

## Results


**Fig. 1 Results of prognostic modeling of glycated hemoglobin level based on glycemic variability data**


**Fig. 2 Results of prognostic modeling of glycated hemoglobin level based on the multiple regression model**

## Results

| Groups | HbA1c at the start of the study | HbA1c at the end of the study | p |
|---|---|---|---|
| Group A | 9,1 [8,2; 9,7] | 7,75 [7,45; 8,05] | 0,016* |
| Group B | 9,5 [8,7; 10,9] | 9,15 [8; 9,8] | 0,001* |

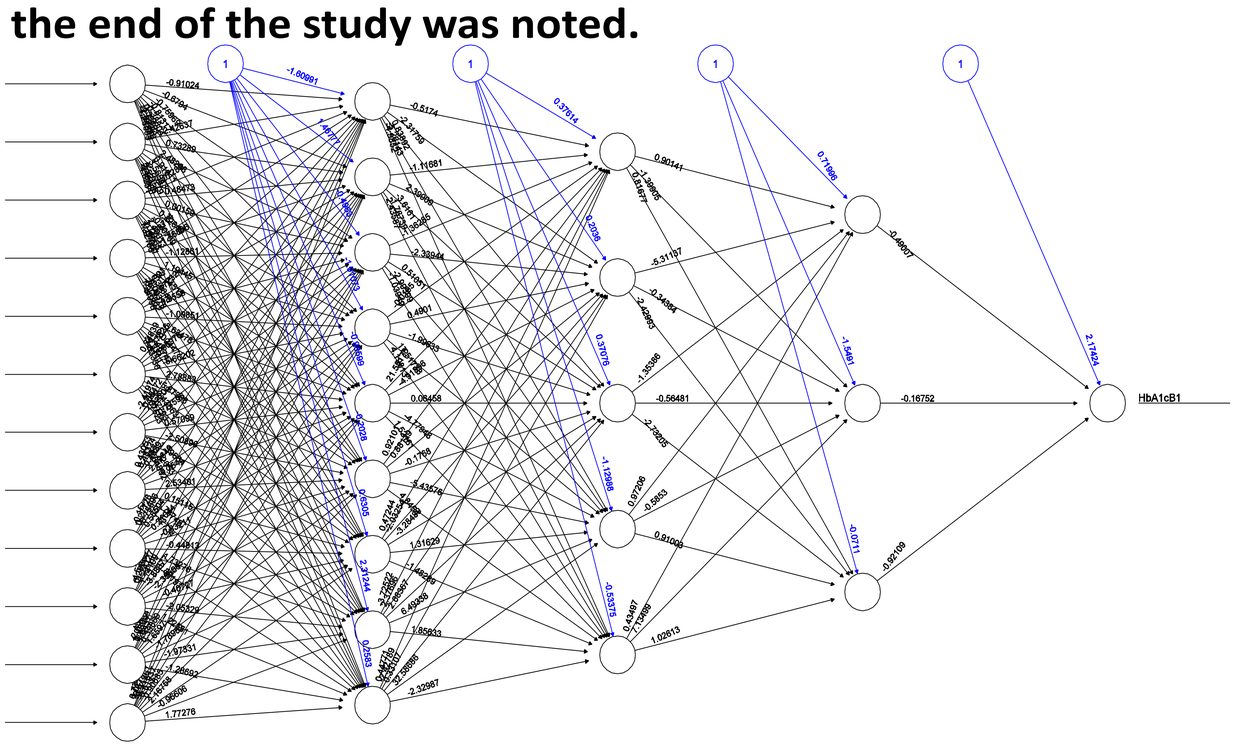
**Note: * - significance of differences between groups (Mann – Whitney U-test, differences are significant at p <0.05); Me is the median, Q1; Q3 - lower; upper quartiles.**

***HbA1c by the end of the study decreased by 1.35% in the remote monitoring group, in the standard observation group, glycated hemoglobin decreased by 0.35%.***

| Glycemic variability indixes | Group A (n - 40) | Group B (n - 40) | p |
|---|---|---|---|
| SD (mmol/l) | 2.08 [1.07; 2.59] | 2.37 [1.68; 3.28] | 0,057 |
| CONGA (mmol/l) | 6.16 [5.62; 6.96] | 8.32 [7.51; 9.17] | 0,001* |
| LI | 4.9 [3.3; 7.99] | 8.32 [6.85; 11.64] | 0,001* |
| J-index | 22.42 [17.08; 28.4] | 46.72 [32.67; 54.41] | 0,001* |
| LBGI | 4.3 [2.99; 5.87] | 7.2 [6.42; 7.85] | 0,001* |
| HBGI | 5.46 [3.04; 8.03] | 8.34 [6.56; 10.32] | 0,001* |
| ADRR | 19.97 [13.34; 27.02] | 23.2 [16.32; 35.82] | 0,230 |
| MAGE (mmol/l) | 4.76 [4.03; 6.32] | 6.17 [5.54; 7.03] | 0,001* |
| Mvalue (mmol/l) | 6.7 [3.23; 10.02] | 11.2 [6.35; 16.53] | 0,005* |
| MAG (mmol/l/hour) | 1.64 [1.14; 2.05] | 2.36 [1.37; 4.28] | 0,010* |

**Note: * - significance of differences between groups (Mann – Whitney U-test, differences are significant at p <0.05); Me is the median, Q1; Q3 - lower; upper quartiles.**

**When using technologies for continuous monitoring of glycemia in patients with type 1 diabetes mellitus, a significant improvement in glycemic variability indicators by the end of the study was noted.**




**The optimal model was based on a multilayer perceptron with three hidden layers and the number of neurons in each layer. The constructed model showed a very high value of the coefficient of determination R2 = 0.987, which indicates a high confidence in predicting the level of HbA1c. When creating a traditional model based on multiple regression, the coefficient of determination was R2 = 0.254, which indicates a low prediction accuracy of the HbA1c level and a higher residual error.**

***The neural network makes it possible to assess the degree of compensation for the disease and provide a personalized approach in treating these patients***