Prediction of the Duration of Inpatient Treatment of Diabetes in Children Based on Neural Networks

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Abstract
The conducted studies related to the substantiation of the knowledge base, which ensures the prediction of the duration of inpatient treatment of diabetes in children based on the use of the developed neural network model of direct communication. The paper proposes an approach and prepares data for predicting the duration of inpatient treatment of diabetes in children. The substantiation of the parameters of the feedforward neural network model for predicting the course of inpatient treatment of diabetes was performed, and the accuracy indicators of the proposed model were also evaluated. The proposed approach to predicting the duration of inpatient treatment of diabetes in children is based on the use of forward propagation neural networks and involves implementing nine stages. The peculiarity of this approach is that the formation of databases and knowledge is carried out based on taking into account the peculiarities of inpatient treatment projects. It is based on a computer analysis of historical data and involves modeling, which provides a systematic consideration of the relationships between factors and the duration of inpatient treatment of diabetes in children. Based on the use of the developed approach, as well as using the prepared data, the parameters of the neural network model of direct communication for predicting the duration of inpatient treatment of diabetes in children are substantiated. The accuracy indicators of the model were evaluated. The proposed rational feedforward neural network model involves two layers (the first is the Dense type with 64 neurons and the ReLU activation function, and the second is the Dense type and 1 neuron). The total number of model parameters is 385. In the proposed model, the learning rate is 0.0001.

Keywords 1
Prediction, neural networks, data preparation, duration, inpatient treatment, diabetes.

1. Introduction

Today, in all spheres of life and activity, people use the knowledge obtained from data. This also applies to medicine and its areas, which is a priority area in various countries of the world. The number of certain types of diseases is increasing. One of them is diabetes [1-3]. According to the World Health Organization, more than 366 million people are sick in the world. According to their forecasts, the number of people with diabetes will increase to 600 million by 2030 [4]. According to the International Diabetes Federation, 2,325,000 diabetes patients are registered in Ukraine, including children under the age of 18 [1].

Diabetes is a serious problem in the world, and the increase in the number of diabetes diseases, in particular among children, poses a challenge to medical professionals to improve the quality of treatment and predict its results during the implementation of relevant projects. One of the approaches to predicting the duration of inpatient treatment of diabetes in children is the use of feed-forward neural networks.

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Neural networks are capable of detecting complex relationships between input data and output, as well as making predictions based on these relationships [5-7]. The use of neural networks to predict the duration of inpatient treatment for diabetes can help medical professionals determine the most effective treatment methods, provide effective planning of treatment projects, and analyze their effectiveness.

Since the duration of diabetes treatment depends on many factors, including height, weight, age, gender, health, and the presence of other diseases, the use of neural networks can provide more accurate predictions, allowing medical professionals to avoid unnecessary procedures and optimize the treatment process [8 -11]. At the same time, the use of neural networks of direct communication makes it possible to obtain models that can estimate the relationship between these factors and the duration of treatment. This makes it possible to make a more accurate and individual forecast of the duration of treatment in children with diabetes.

2. Analysis of published data and problem setting

Management tasks related to the development of new and improvement of existing approaches to the implementation of forecasting processes, based on the consideration of multiple influencing factors and the use of artificial intelligence methods, are now widely used in all subject areas [12-15]. This is especially relevant for medical projects, the implementation of which requires taking into account the specific condition of patients and determining the duration of their treatment, which depends on the configuration of the hospital and the availability of beds.

In scientific works [16-19], an analysis of the state of use of the intelligent data analysis toolkit was carried out and the expediency of its use for solving management problems, including forecasting, was substantiated. This toolkit involves the use of traditional models of statistical analysis, which have limited capabilities for processing large data.

Analyzing the task of predicting the duration of inpatient treatment of diabetes in children, should be noted that it is quite difficult due to the multifactorial individual characteristics of each patient [20-24]. It is also worth noting that the use of traditional methods of statistical data analysis may not be effective enough when working with large data sets. This is due to the difficulties caused by the presence of complex dependencies between individual factors, which should be taken into account when forecasting future values based on historical data. Therefore, taking into account the above, it should be noted about the feasibility of using machine learning algorithms and artificial neural networks, which can be useful for solving this problem and provide the appropriate accuracy.

Some authors in their works [25-27] point out that neural networks can be an effective tool for finding complex relationships between factors, which will ensure the prediction of future values based on historical data. Among them, neural networks of direct communication are the most accessible and at the same time simple. In works [28-30], their authors note that neural networks of direct communication can be especially useful for forecasting in medicine. In particular, this applies to predicting the duration of inpatient treatment of diabetes in children. At the same time, they can work with multidimensional data and reveal complex relationships between external factors, such as patient characteristics and disease history, etc.

Therefore, the use of artificial neural networks of direct communication can increase the accuracy of predicting the duration of inpatient treatment of diabetes in children. At the same time, to solve this scientific and applied problem, it is necessary to collect and prepare data that will justify the parameters of the neural network model of direct communication. Conducted research in this direction is the basis for the implementation of management processes of planning treatment projects and contributes to the improvement of their results.

3. The purpose and objectives of the study

The purpose of the work is to substantiate the knowledge base that provides a prediction of the duration of inpatient treatment of diabetes in children based on the use of the developed neural network model of direct communication.

To achieve the goal, the following tasks should be solved:

1. propose an approach and prepare data for predicting the duration of inpatient treatment of diabetes in children;
2. to justify the parameters of the neural network model of direct communication for predicting the duration of inpatient treatment of diabetes and to evaluate its accuracy indicators.

4. An approach to predicting the duration of inpatient treatment of diabetes in children and data preparation

Let's consider the main stages of developing a model for predicting the duration of inpatient treatment of diabetes in children based on the use of neural networks of direct communication (Fig.1).

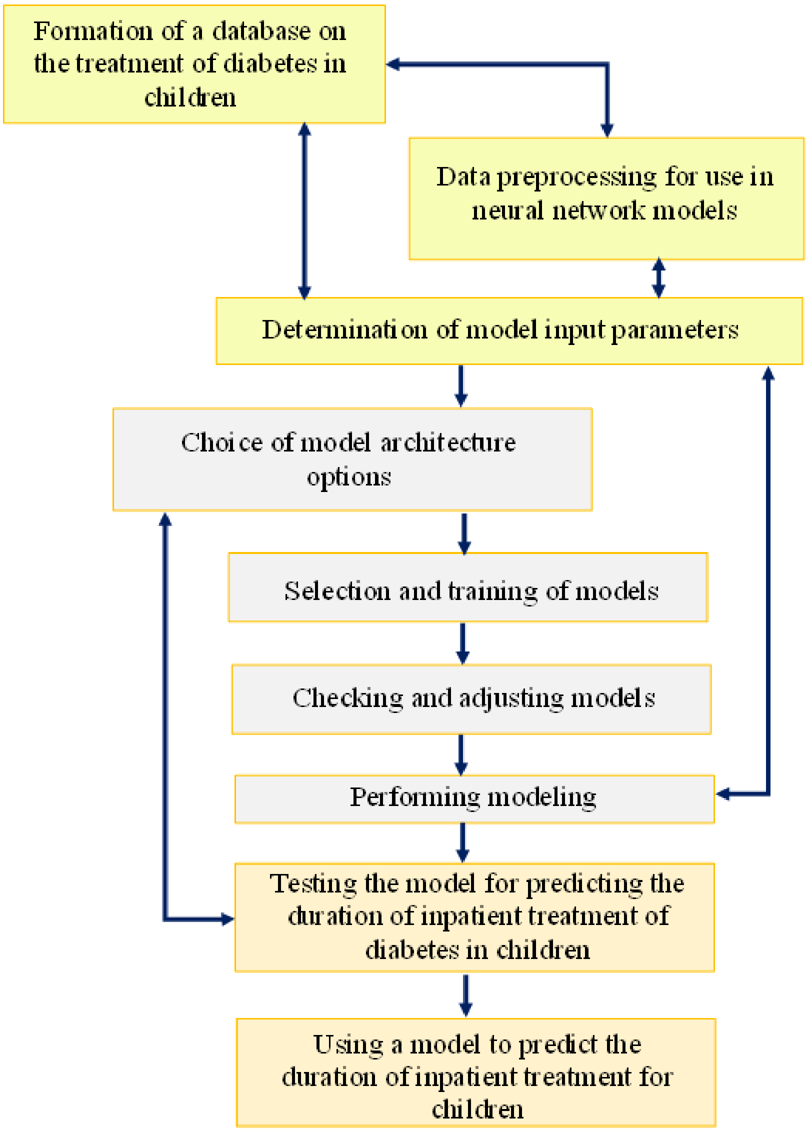


Figure 1: Stages of development of a model for predicting the duration of inpatient treatment of diabetes in children based on the use of neural networks of direct communication

The stage of forming a database on the treatment of diabetes in children is key to the successful development of a model for predicting the duration of inpatient treatment. For this, a sufficient volume of data on the process of treatment of sick children with diabetes should be collected according to individual attributes characterizing the factors that determine the duration of treatment. One method of data collection is the use of Electronic Medical Records (EMR) data. With the help of EMR, 779 instances of data on inpatient treatment (Lviv, Ukraine) of diabetes in children (Fig. 2) were obtained, which are distributed by attributes: 1) date of hospitalization (Date_hospitalization); 2) date of discharge from the hospital (Date_discharge); 3) treatment department (Department); 4) date of birth of the patient (Date_birth); 5) place of residence (Residence); 6) patient's temperature (Temperature); 7) height of the patient (Height); 8) duration of treatment (Bed_days); 9) gender of the patient (Human_gender) 10) weight of the patient (Weight); 11) type of hospitalization (In_hospital); 12) disease state (Condition); 13) type of settlement (Type_settlement); 14) result of treatment (Result).

	Date_hospitalization	Date_discharge	Department	Date_birth	Temperature	Height	Bed_days	Human_gender	Weight	In_hospital	Condition	Type_settlement	Result	Years
0	09-05	09-05	Pediatrics	2010-06-22	36.6	0.0	9	Women	0.0	in a planned manner	Diabetes, type 1, was first discovered	Village	NaN	4
1	05-11	08-11	Pediatrics	2009-08-15	36.6	0.0	24	Man	0.0	in a planned manner	Diabetes, type 1, was first discovered	City	NaN	4
2	08-09	08-09	Pediatrics	2009-06-28	36.7	1140	22	Women	18.4	in a planned manner	Diabetes, type 1, was first discovered	Village	NaN	5
3	08-20	08-20	Pediatrics	2003-08-27	36.6	1380	11	Women	26.0	in a planned manner	Diabetes, type 1, was first discovered	City	NaN	10
4	08-18	08-18	Reanimation	2008-10-31	36.8	0.0	13	Man	27.7	for urgent indications	Diabetes, type 1, was first discovered	City	NaN	5

Figure 2: A fragment of the database on inpatient treatment of diabetes in children

The Jupyter Notebook interactive programming environment was used to collect and analyze data on the treatment of diabetes in children. It allows you to combine text, code, and the result of the execution in a single document. Using Jupyter Notebook allows data analysis and visualization of results in a developer-friendly format and facilitates more efficient work with data.

In the data preprocessing step, data scaling was applied. This is an important procedure before training neural network models to ensure that each attribute is equally important. In particular, one of the approaches to data scaling was used - normalization, or minimax scaling. This approach creates the transformed attribute values so that they are between 0 and 1. The minimum data scaling formula for each attribute X_i is:

$$X_i' = \left(X_i - min\left(X_i\right)\right) \; / \; \left(max\left(X_i\right) - min\left(X_i\right)\right), \tag{1}$$

where X_i – the current value of the attribute; $min\left(X_i\right)$ – the minimum value of the attribute in the data, $max\left(X_i\right)$ – the maximum value of the attribute in the data, X_i' – the scaled value of the attribute.

In addition, one-hot encoding of categorical variables was applied to convert them into numeric data that can be used in neural network models. For each unique value of a categorical change, a separate binary change is created. If the categorical variable has unique values, then after applying one-hot encoding, binary variables are also created. Each of these variables has a value of 1 if the corresponding value is unique to the data and 0 if it is not used. For example, if we have a categorical change "gender of the patient (Human_gender)" with two unique values ("Ч" and "Ж"), then after applying one-hot encoding we get two binary changes, where 1 indicates the female gender of the patient and 0 for the male gender of the patient.

The special scikit-learn library of the Python programming language was used for data preprocessing.

Data cleaning is considered an important step before creating neural network models to avoid using incorrect or missing data. Various methods can be used to clean the data, such as removing rows with missing values, filling missing values with the mean or median, and removing duplicate rows. To fill in missing values, you can use the fillna() method, which allows you to fill in missing values in data columns based on a given criterion, such as the mean or median. As a result of this stage, data were prepared, a fragment of which is presented in Table 1.

Table 1
A fragment of prepared data for predicting the duration of inpatient treatment of diabetes in children based on the use of neural networks of direct communication

Patient	Department	Temperature	Height	Humangender	Weight	Inhospital	Condition	Typesettlement	Result	Years	Bed_days
–	X1	X2	X3	X4	X5	X6	X7	X8	X9	X10	Y1
3	0	36.6	138.0	0	26.0	0	6	0	3	10	11
6	0	36.6	103.5	0	19.4	0	6	1	3	4	13
7	0	36.6	173.0	1	49.0	0	6	0	3	14	6
…	…	…	…	…	…	…	…	…	…	…	…
12	0	36.6	111.0	1	17.4	0	6	0	3	6	8
18	1	36.6	139.0	0	31.7	1	6	0	3	9	7

At the next stage, the input parameters of the model for predicting the duration of inpatient treatment of diabetes in children are determined based on the use of neural networks of direct communication. This step consists in selecting the attributes most correlated with the target attribute «Bed_days» using a correlation matrix. For each input factor X_i (according to Table 1), we find their average value:

$$\bar{X}_i = \frac{1}{N}\sum_{i=1}^{N} X_{ij}, j = 1, m, \tag{2}$$

After that, we calculate the correlation matrix K_{ij}, the elements of which are determined by the formula:

$$K_{ij} = \frac{\operatorname{cov}\left(X_{ij}, Y_1\right)}{\sigma\left(X_{ij}\right), \sigma\left(Y_1\right)}, \tag{3}$$

where $\operatorname{cov}\left(X_{ij}, Y_1\right)$ – the covariance between factor X_{ij} inputs and the target attribute Y_1.

The covariance between the input factor X_{ij} and the target attribute Y_1 is determined by the formula:

$$\operatorname{cov}\left(X_{ij}, Y_1\right) = \frac{1}{N-1}\sum_{l=1}^{N}\left(X_{li} - \bar{X}_i\right)\left(X_{lj} - \bar{X}_j\right), i, j = 1, n, \tag{4}$$

Table 2
Results of determining the correlation of the target attribute «Bed_days» with each other attribute

Attribute	Correlation coefficient	Attribute	Correlation coefficient
Department	0.003	In_hospital	0.118
Temperature	0.052	Condition	0.417
Height	0.18	Type_settlement	0.003
Human_gender	0.003	Result	0.050
Weight	0.2	Years	0.217

A correlation matrix displays the relationships between attributes in a dataset (df). For the target attribute «Bed_days», the correlation with each other attribute was calculated using formula (3). The obtained results are presented in Table 2.

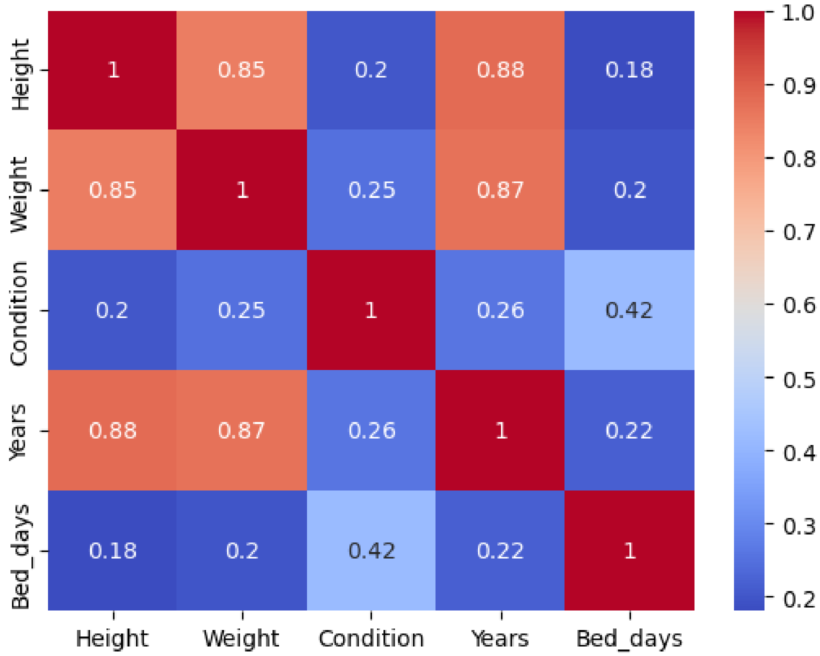


Figure 3: Correlation matrix between factor inputs and target attribute «Bed_days»

Based on the data in Table 2, it should be noted that most of the attributes have a weak correlation with the «Bed_days» attribute. This suggests that they should not be used as input parameters of a neural network model. As a result of data cleaning, we built a correlation matrix in the form of a thermal diagram, which reflects the input parameters of the model (Fig. 3).

5. Justification of the parameters of the neural network model for predicting the duration of inpatient treatment of diabetes

In our research, it is accepted that the architecture of the model is chosen according to the features of the requirements for the task of predicting the duration of inpatient treatment of diabetes. In this case, a model with a simple neural network with a variable number of hidden layers having 64 neurons is adopted. It is known [7] that this architecture of the neural network model can be effective if there is not a lot of data and they have a sufficiently simple structure. In addition, our research compared models from 2 to 7 layers (Fig. 4). It is impractical to increase their number to avoid retraining the model.

In recent years, many researchers have used the ReLU (rectified linear unit) activation function. Our research uses the ReLU activation function, which allows the model to read raw data and extract useful features from it. Mathematically, it can be described by the formula:

$$\sigma(X_i) = \max(0, X_i). \tag{5}$$

You can display the ReLU activation function in the form of a graph (Fig. 5).

Using the ReLU function significantly increases the convergence speed of stochastic gradient descent compared to sigmoid and hyperbolic tangent. This is due to the linear nature, and at the same time, there is no saturation of this function.

The output layer has one neuron and no activation function. This indicates that the model solves the problem of regression, where it is necessary to predict the value of a numerical value - the duration of inpatient treatment of diabetes in children.

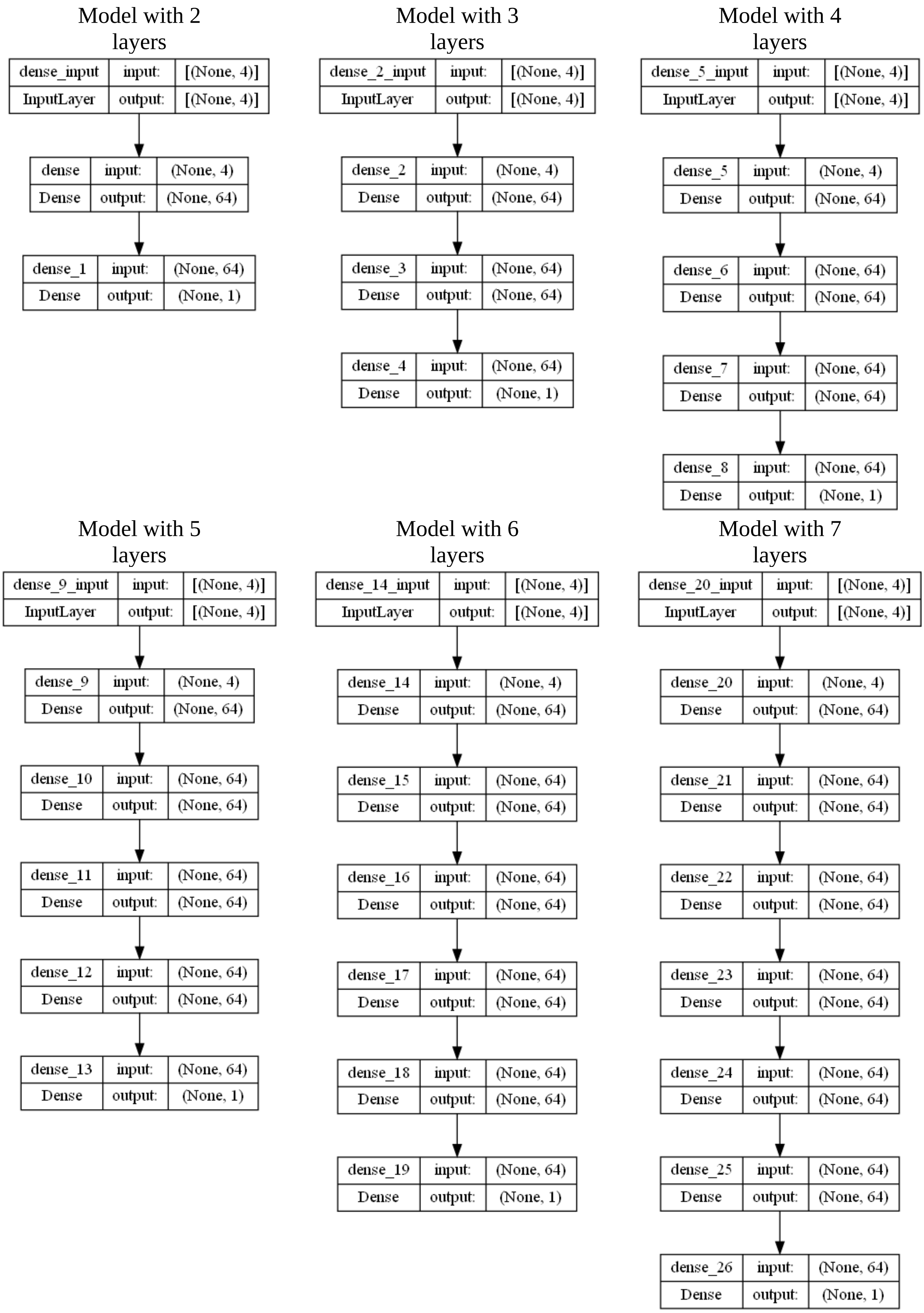


Figure 4: The architecture of the researched feedforward neural network models for predicting the duration of inpatient treatment of diabetes in children

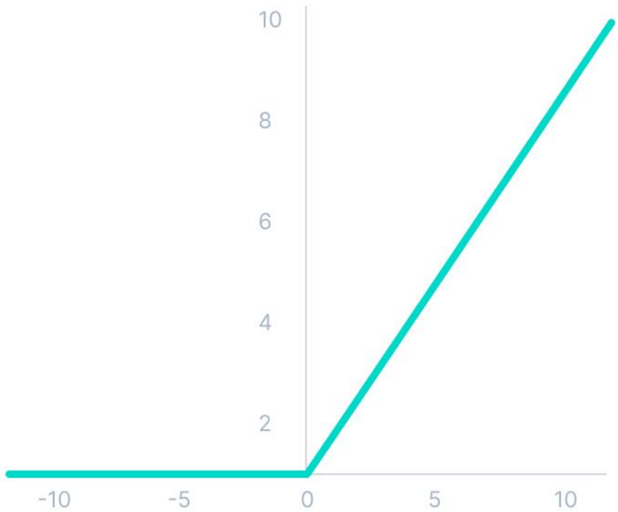


Figure 5: ReLU activation function

We have chosen the MSE and MAE metrics, which allow us to monitor the quality of the model during training and testing, and also help to extend the performance of the model in various aspects. In particular, MSE (Mean Squared Error) is an indicator for assessing the quality of regression models, which provides the calculation of the mean squared difference between the predicted values using the models and the true values:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(Y_i - \hat{Y}_i\right)^2 . \quad (6)$$

where Y_i – is the true value of the duration of inpatient treatment of diabetes in children, days; $\hat{Y}_i$ – duration of inpatient treatment of diabetes in children, days; N –the number of examples in the data set, units.

MAE (Mean Absolute Error) is an indicator for evaluating the quality of regression models, which provides the calculation of the average value of the difference between the predicted values of the models and the true values:

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i - \hat{Y}\right| . \quad (7)$$

It should also be noted that in our research, the MSE loss functions and the Adam optimizer were chosen with a different value of the learning rate (learning rate) from 0.0001 to 0.1, which allows us to restore the propagation of errors and reduce losses during model training. Adam (Adaptive Moment Estimation) is an adaptive optimizer with moments that are widely used for training neural networks [5]. It combines two methods, namely gradient descent with moments (Momentum) and adaptive gradient descent (RMSProp). The Adam optimizer uses the first and second moments of the gradient to adaptively and quickly update the weights and biases. Moment values are calculated at each optimization step by smoothing the gradients. The value of smoothing is controlled by parameters β_1 and β_2. Additionally, the Adam optimizer uses a parameter to stabilize the denominator when propagating the expression to update the weights:

$$\omega_{t+1} = \omega_t - \frac{\eta}{\sqrt{\hat{\upsilon}_t} + \varepsilon}\hat{\mu}_t , \quad (8)$$

where ω_t – the vector of weights at step t; η – speed of learning; $\hat{\mu}_t$, $\hat{\upsilon}_t$ – the estimate of the first and second moments of the gradient at step t; ε – a small stabilization plugin that ensures that division $\sqrt{\hat{\upsilon}_t}$ does not lead to division by 0.

The formula for estimating the moments of the gradient of the Adam optimizer is determined by the formulas:

$$\hat{\mu}_t = \beta_1\mu_{t-1} + (1-\beta_1)q_t , \quad (9)$$

$$\hat{v}_t = \beta_2 \mu_{t-1} + (1-\beta_2) q_t^2, \quad (10)$$

where q_t – the gradient at step t; β_1, β_2 – are smoothing parameters, usually β_1=0.9 and β_2=0.999.

The Adam optimizer is a well-balanced optimization algorithm for machine learning tasks and is recommended by many researchers as a silent optimizer for training deep neural networks.

In general, the selected variants of the model architecture and a set of their parameters are the basis for solving the regression problem - predicting the duration of inpatient treatment of diabetes in children using neural networks. However, it is worth paying attention to the fact that the parameters of the model should be optimized to avoid its overtraining and to substantiate the optimal architecture to increase the accuracy of predicting the duration of inpatient treatment of diabetes in children.

6. Results of the substantiation of the neural network model for predicting the duration of inpatient treatment of diabetes and evaluating its accuracy indicators

Based on the proposed variants of the architecture of the studied neural network models of direct communication, models were created and simulations were performed to predict the duration of inpatient treatment of diabetes in children. The simulation results show (Fig. 5) that the loss of test data for each of the models changes differently with the increase in the number of epochs. At the same time, they believe that the smaller the loss, the better the model.

Table 3
Results of determination of loss indicators on test data

Variant of the model	Model learning speed, ms/step	Test Loss model
Model 2	2	0.0488
Model 3	2	0.0498
Model 4	3	0.0483
Model 5	2	0.0484
Model 6	2	0.0469
Model 7	2	0.0465

The following conclusions can be drawn from Table 3. The slowest to learn was model 4, which learned at 3ms/step, while all other models learned at 2ms/step. Models 6 and 7 with losses of 0.0469 and 0.0465, respectively, have the best loss indicators on test data. The worst performance was shown by model 3 with a learning speed of 2 ms/step and loss on test data of 0.0498. In general, we can say that the learning speed of the model does not always correlate with its accuracy, so it is necessary to pay attention to the final indicators on the test data, which are presented in Fig. 6.

It was established that all variants of the studied models have fairly low losses, which indicates their effectiveness. It is also important to pay attention to the difference between the losses on the training and test data. If the specified difference is significant, this may be a sign of retraining the model on the training data. Metrics such as mean absolute error (MAE) and mean squared error (MSE) accuracy were used to evaluate the losses to gain a more complete insight into the performance of the models.

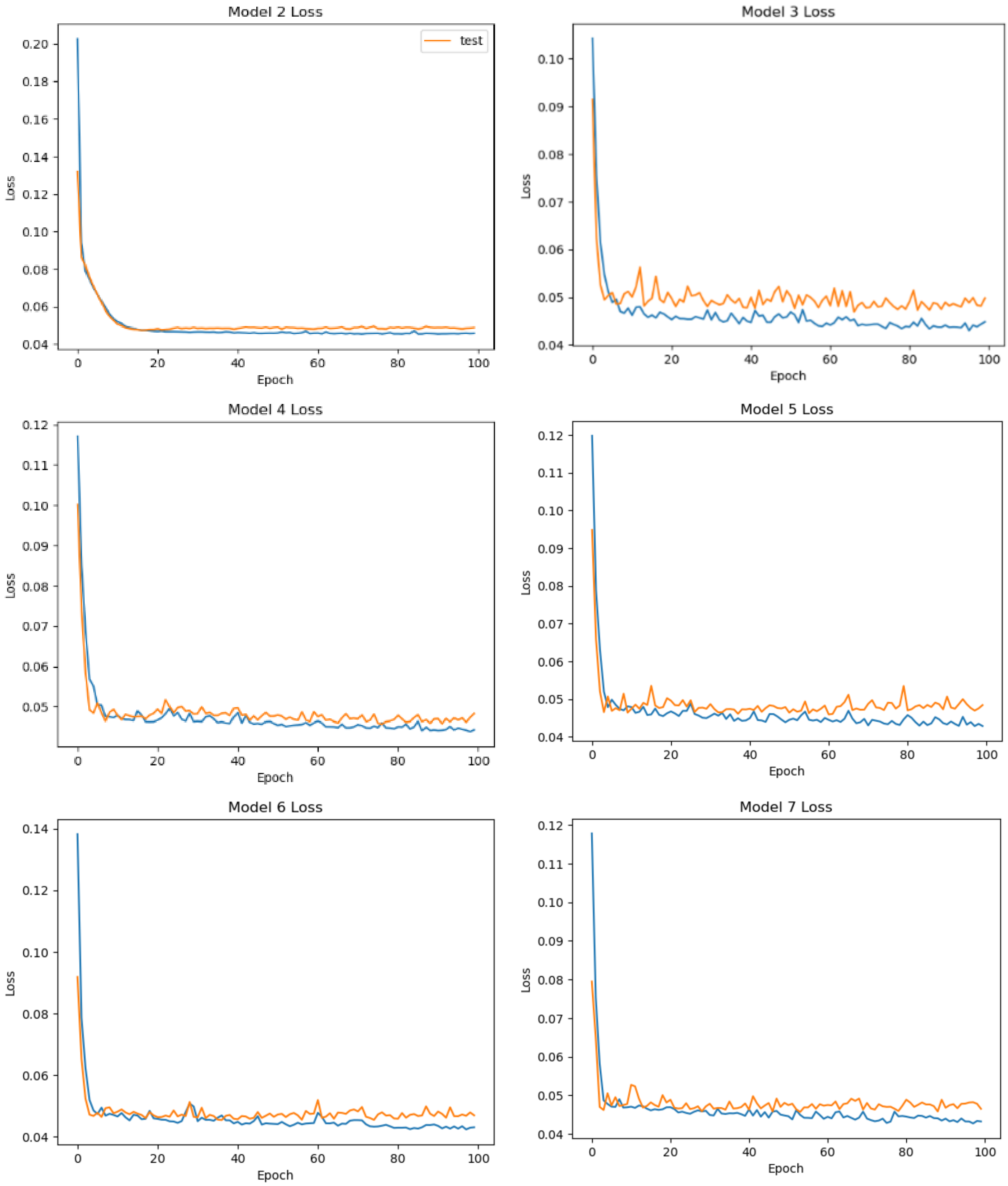


Figure 6: Dependencies of the change in losses of the studied models on the number of training epochs according to the mean squared error (MSE)

Based on the obtained dependencies, it was established that the best results are shown by model 2, which is sufficient for learning 50 epochs (Fig. 7, a). All other models are subject to overtraining. Model 2 has the parameters presented in Table 4.

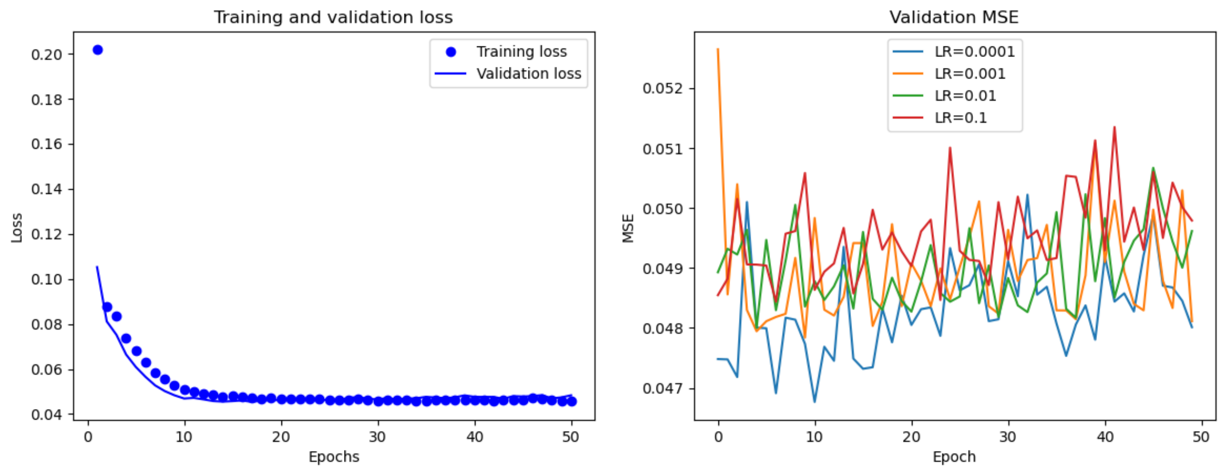
We use the selected model 2 for further research related to the optimization of its parameters (Fig. 6, b). At the same time, we set different learning rate values for the Adam optimizer:

$$learning\_rates = [0.0001,\ 0.001,\ 0.01,\ 0.1]. \tag{11}$$

Table 4
Results of determining the parameters of model 2 «sequential_6»

Layer (type)	Output Shape	Param #
dense_27 (Dense)	(None, 64)	320
dense_28 (Dense)	(None, 1)	65
	Total params: 385	
	Trainable params: 385	
	Non-trainable params: 0	

Table 3 shows that the proposed model consists of two layers. The first layer is of Dense type with 64 neurons and ReLU activation function, and the second layer is also of Dense type and 1 neuron, which is used for the regression problem because the output value is a single numerical value of the duration of diabetes inpatient treatment. The total number of model parameters is 385, which includes the number of neurons, offsets, and inputs to each neuron. In addition, all parameters are subject to learning.



a) b)

Figure 7: The results of the estimation of losses based on the mean squared error (MSE) during the training of the basic model (a) and the model at different values of the learning rate for the Adam optimizer (b)

Based on the research results, it was established that the model with the smallest value shows the best results. Therefore, the proposed rational neural network model of forward communication for predicting the duration of inpatient treatment of diabetes in children has an architecture consisting of two layers (the first is the Dense type with 64 neurons and the ReLU activation function, and the second is the Dense type and 1 neuron). The total number of model parameters is 385. In the proposed model, the learning rate is 0.0001. This value is set experimentally and is small, which can help avoid divergence or skewing of the model.

7. Conclusions

1. The proposed approach to predicting the duration of inpatient treatment of diabetes in children is based on the use of forward propagation neural networks and involves nine stages. The peculiarity of this approach is that the formation of databases and knowledge is carried out based on taking into account the peculiarities of inpatient treatment projects thanks to the computer analysis of historical data and the execution of simulations. This ensures a systematic consideration of the interrelationships between the factors and the duration of inpatient treatment of diabetes in children. The described

approach is the basis of qualitative data preparation and increases the accuracy of neural network models for predicting the duration of inpatient treatment of diabetes in children.

2. Based on the use of the developed approach, as well as using the prepared data, the parameters of the neural network model of direct communication for predicting the duration of inpatient treatment of diabetes were substantiated and its accuracy indicators were evaluated. The proposed rational feedforward neural network model for predicting the duration of inpatient treatment of diabetes in children has an architecture that involves two layers (the first is the Dense type with 64 neurons and the ReLU activation function, and the second is the Dense type and 1 neuron). The total number of model parameters is 385. In the proposed model, the learning rate is 0.0001. Further research should be conducted on the development of a decision support system that will provide a solution to the problem of planning diabetes treatment projects in children using a valid feed-forward neural network model to predict the duration of their inpatient treatment.

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