

Artificial intelligence Integration in the diagnosis, prognosis and diabetic neovascular glaucoma treatment

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Abstract

This work is focused on key aspects of the diagnosis, prognosis and treatment of neovascular glaucoma of diabetic origin based on machine learning approaches and, in particular, various architectures artificial neural models. An analysis of the relevance, priority provisions and advantages of using machine learning methods is carried out, the existing approaches used in modern literature in the context of the topic under study are considered, the specifics of their integration into the process of diagnostic analysis of the feature space of an aggregated and labeled by the authors data set on patients with visual problems are described, in particular, those suffering from neovascular glaucoma of diabetic origin. A correlation analysis of input features was carried out, 3 different models of artificial neural networks were built, trained and tested, metrics for assessing the accuracy of their work were experimentally calculated and studied, and statistical indicators were determined, including errors and losses, characterizing their generalizing ability. Analysis of the results obtained from the studies made it possible to identify the prevailing input features and evaluate their impact on the target output variable and the overall significance in the feature space of the data set, as well as to establish the most suitable models for data analysis in terms of their accuracy and speed. The conducted research made it possible to establish the fact of a greater degree deep learning artificial neural networks models fully connected adaptability for the analyzed data set.

Keywords

Artificial intelligence, neovascular glaucoma, diagnosis eye treatment, neural networks, data analysis, data mining, machine learning

1. Introduction

Currently, the volumes of heterogeneous information collected during the examination of patients in various fields of medicine are constantly increasing [1]. This is due to the tendency to integrate various technical means and software systems for diagnosing human body organs diseases, especially vision organs, which make it possible to measure and process numerous quantitative and qualitative parameters characterizing the nature, stage and disease complexity. The development of artificial intelligence (AI) technology in medical decision making allows for the simultaneous analysis of an infinite variables number.

AI technologies provide improving patient care in medical decision making and require physicians and computer scientists to have a successful mutual understanding of both technology and medical practice. Recently, thanks to AI methods, significant advances have been made in the diagnosis of ophthalmic pathologies. With their help, data from visual fields, optic nerve structure (for example, obtained using optical coherence tomography (OCT), biomechanical ocular properties

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and their combination are successfully analyzed and classified to determine the severity of the disease, its progression and/or referral for specialized treatment.

Diagnostic search algorithms for patients with glaucoma have undergone further changes, becoming more and more complex, and to improve existing methodologies it is necessary to use more reliable classification diseases signs. A significant contribution in this direction is made by modern methods and models for assessing and predicting the effectiveness of patient treatment, actively developed and implemented by specialists in the field of prevention and eye pathologies diagnosis. It should be noted that in the process of inflammation assessing indicators and intraocular circulation in patients collected during statistical data examination, an important aspect of the procedure for their analysis is indicators diagnostic significance [2]. This is relevant both for identifying and formalizing key factors that have the greatest impact on the visual organs integral state, and for developing and implementing preventive measures and developing protocols ophthalmic diseases effective treatment.

Due to the lack of clearly identified patterns and correlations in the feature space of aggregated diagnostic data for the patients' vision organs as well as due to the high degree of uncertainty in mutual influence, carrying out the processes of assessing and analyzing data in a manual format is difficult and labor-intensive. Therefore, it is rational to use modern methods of data mining, in particular machine learning (ML) algorithms, in order to automate the process of searching for hidden patterns in data and assessing the level of feature space diagnostic significance, which is especially justified in the presence of large data volumes [3]. This allows us to provide solutions to various applied problems in the field of ophthalmology. In particular, it helps to increase the efficiency of the decision support process for assessing the patient's condition and the use of targeted treatments for diabetic neovascular glaucoma [4] through the use of ML models to automate data research and search for individual signs correlations with each other. There are significant results from the use of ML in the analysis of such pathological eye conditions as diabetic retinopathy, age-related macular degeneration, macular edema, glaucoma, cataracts, etc. In this case, color fundus photographs, images obtained during fluorescein angiography and autofluorescence, OCT scans, fields of view [5, 6, 7].

The defining characteristic of ML algorithms is the quality of their predictions, which improves with experience. The more data provided, the better the forecasting model. In this context, difficulties arise due to various factors, including [8]:

- insufficiently high generalization ability of classical ML models;
- absence of memory effect in models;
- insufficient adaptability of models to data, taking into account the specifics under consideration;
- the need to compile ML models ensembles to ensure a higher degree of accuracy of the forecast values they generate;
- time costs for preliminary data scaling and preprocessing.

In this regard, a perspective way is to use more advanced, modern and efficient deep ML models, which are artificial neural networks (ANN) of various architectures, topologies and hierarchically interconnected.

An important aspect in the problem we are considering is the study of different ML models among themselves to experimentally identify an estimate of the most appropriate hyperparameters values, which affect the output metrics for assessing used models quality [9]. In this context, an approach based on deep learning and ANN makes it possible to more effectively solve classification and regression problems, taking into account the specifics of the application area under consideration, as well as to form various hybrid models that can have greater generalization ability and be more flexible in comparison with classical ML approaches, eliminate the imbalance of the feature space, perform the functions of data normalization and reduce the likelihood of overtraining models through the introduction of regularization methods [1]. An additional important aspect is the ability

to minimize the risk of generating contradictory results from ANN models, for example, by integrating bagging and boosting techniques when creating model's ensembles. In this regard, ANN using is more appropriate within the framework of the topic under consideration.

2. Analysis existing researches

In the medical field, there is an active use of various approaches, most often based on statistical methods and ML models for the analysis and evaluation of experimentally obtained results of diagnosis and various diseases treatment, including vision organs. Thus, the authors [10] adapt ML learning algorithms to solve the classification problem, achieving significant results of both high accuracy and completeness on the collected dataset of ophthalmological indicators. However, the data analyzed by the authors is often not complete and contains signs of synthesized subsamples, which complicates the procedure for assessing metric indicators. In [11], the authors use fully connected ANN models, comparing their work with each other and existing methods for classifying ML data, which is appropriate to demonstrate the capabilities and performance of these models in the context of their deployment in real diagnostic software and hardware tools for data analysis and evaluation.

The effectiveness of using ML was also established by the authors [12] in studies in the field of treating respiratory system evaluating methods when analyzing the significance of individual signs and diseases course intensity indicators.

According to a number of authors [13, 14], the use of methods for preventive intelligence medical data analysis in the context of assessing statistical indicators and correlations between individual data sets features allows the formation of an effective consistent data basis, thus organizing the process of automatic dimensionality reduction. As follows from the works [15, 16] on the use of ML in practice, the most effective are algorithms united in committees, this allows for models balancing and error values averaging for various metrics.

Thus, analyzing the research results in the reviewed authors works [10-16], it should be noted that more often they consider the possibility of using statistical approaches, as well as ML and ANN models, primarily to solve classification and regression problems in a heterogeneous feature space. However, outside the scope of research, questions remain related to assessing the individual medical indicators diagnostic significance, identifying correlations between input signs and assessing their specific weight values in the context of considering ophthalmological disease problems in patients with diabetic neovascular glaucoma.

The relevance of such studies is undoubted, due to the increasing disability of patients with this pathology throughout the world. In this regard, this work goal is to create and study different ANN models with generalization abilities and architecture for assessing the significance of features based on the collected data set on diagnostic indicators of inflammation and intraocular circulation in patients with diabetic neovascular glaucoma.

3. Collected data set description

The created set of the most significant target input and output features with medical interpretation was selected as a data set for analysis in applying ML process.

A retrospective cohort study of 127 patients (127 eyes) with a painful form of neovascular glaucoma (NVG) of diabetic origin was conducted at the Institute of Eye Diseases and Tissue Therapy named after V.P. Filatov NAMS of Ukraine. The study protocol complied with the principles of the Declaration of Helsinki and was approved by the local institute's bioethical committee. Written informed consent was obtained from all study participants. The average age of patients is 65.0 years (62-68).

The patients had uncontrolled intraocular pressure - IOP ≥ 30 mm Hg, and also had ocular pain syndrome. The main criterion for assessing the success of treatment was control of IOP and achieving

its reduction by 20% from the initial value after 12 months of observation and maintaining best-corrected visual acuity (BCVA) - “success of treatment”.

The preoperative visit (V0) was carried out on the eve of transscleral (TSC) cyclophotocoagulation (CPC), which was performed according to standard techniques. The laser power ranged from 850 to 1500 mW (Me 1100 mW), exposure time was 1.5-2 seconds, and laser coagulates average number was 22. In all patients, the need for repeat CFC TSC was determined at each postoperative visit. The criterion for repeated laser treatment was maintaining high IOP values. Preoperative laboratory parameters were determined: neutrophils (N), lymphocytes (L), platelets (Throm), monocytes (M), glycosylated hemoglobin (HbA1c, %), volumetric intraocular circulation (RQ, ‰) according to rheophthalmography.

The systemic immune inflammation index ($SII = \text{Throm} \times [N/L]$) and systemic inflammation response index ($SIRI = N \times [M/L]$) were calculated. The SIRI and SII scores were further divided into quartiles, and the RQ score into quintiles. The data has been imported, divided into input and output characteristics.

The target variable is the indicator “success of treatment”, which is a binary attribute. A fragment of the generated dataset is shown in Fig. 1. The results of related correlation analysis of the most significant features are shown in Fig. 2.

Name	Type	Missing	Statistics		
complications after CPT	Integer	0	0	1	0.591
LYM (109/L)	Real	0	Min 1.500	Max 2.400	Average 1.857
SIRI	Real	0	Min 0.460	Max 1.150	Average 0.727
SIRI kvartils	Integer	0	Min 1	Max 4	Average 2.244
SII	Real	0	Min 338	Max 673.900	Average 474.002
SII kvartils	Integer	0	Min 1	Max 4	Average 2.394
RQ critical - 0	Integer	0	Min 0	Max 1	Average 0.551
RQ V0	Real	0	Min 1.400	Max 5.650	Average 3.168
Success VOT	Polynominal	0	Least false (44)	Most true (83)	Values true (83), false (44)

Figure 1: Fragment of the input data set for analysis

There is some imbalance in the output class values, which is not critical for research, and therefore the use of synthetic balancing methods is not advisable due to introducing additional noise risk into the data.

As part of the reconnaissance data analysis, a correlation analysis of the feature space was performed in order to identify obvious patterns between individual input variables. How can we note the indicators SIRI, SIRI quartiles. SII, SII quartiles have a high correlation with each other and with another input feature HbA1, which can introduce additional noise into the operation of models, and therefore it is necessary to take into account the nature of the influence of these features on the output target variable.

The correlation analysis showed a high positive relationship between the success of treatment and the indicators HbA1c ($r = 0.751$), SII ($r = 0.876$), SIRI quartiles ($r = 0.874$), IOP V0 ($r = 0.611$) and a high negative relationship with the RQ quintiles indicator ($r = -0.807$).

Attribut...	sex	age	HbA1	laserc...	Caute...	Laser ...	V0 VOT	GZ V0	com...	LYM (...	SIRI	SIRI ...	SII	SII kv...	RQ cr...	RQ V0	Succes...
sex	1	-0.048	0.021	0.206	-0.056	0.069	0.102	0.131	-0.078	0.014	0.016	0.048	-0.024	-0.009	-0.097	0.148	-0.026
age	-0.048	1	-0.273	-0.241	-0.018	-0.021	-0.041	-0.295	0.103	-0.202	-0.156	-0.103	-0.074	-0.081	0.183	0.285	-0.115
HbA1	0.021	-0.273	1	-0.189	0.306	0.363	0.573	-0.219	0.355	-0.149	0.815	0.758	0.774	0.633	-0.620	-0.156	0.751
lasercou...	0.206	-0.241	-0.189	1	0.004	-0.191	-0.193	0.349	-0.163	0.133	-0.163	-0.203	-0.209	-0.263	0.062	-0.110	-0.230
Cauteriz...	-0.056	-0.018	0.306	0.004	1	-0.093	0.141	-0.153	0.193	-0.040	0.316	0.301	0.356	0.377	-0.203	-0.187	0.304
Laser 81...	0.069	-0.021	0.363	-0.191	-0.093	1	0.251	-0.066	0.209	-0.144	0.360	0.409	0.410	0.365	-0.213	0.046	0.332
V0 VOT	0.102	-0.041	0.573	-0.193	0.141	0.251	1	-0.494	0.504	-0.115	0.643	0.590	0.657	0.563	-0.430	-0.123	0.611
GZ V0	0.131	-0.295	-0.219	0.349	-0.153	-0.066	-0.494	1	-0.574	0.107	-0.385	-0.397	-0.379	-0.334	0.279	0.018	-0.344
complica...	-0.078	0.103	0.355	-0.163	0.193	0.209	0.504	-0.574	1	-0.148	0.536	0.465	0.510	0.408	-0.397	-0.086	0.472
LYM (10...	0.014	-0.202	-0.149	0.133	-0.040	-0.144	-0.115	0.107	-0.148	1	-0.259	-0.281	-0.265	-0.307	0.025	-0.034	-0.183
SIRI	0.016	-0.156	0.815	-0.163	0.316	0.360	0.643	-0.385	0.536	-0.259	1	0.954	0.917	0.813	-0.744	-0.138	0.874
SIRI kvar...	0.048	-0.103	0.758	-0.203	0.301	0.409	0.590	-0.397	0.465	-0.281	0.954	1	0.874	0.806	-0.683	-0.061	0.822
SII	-0.024	-0.074	0.774	-0.209	0.356	0.410	0.657	-0.379	0.510	-0.265	0.917	0.874	1	0.893	-0.682	-0.047	0.876
SII kvartis	-0.009	-0.081	0.633	-0.263	0.377	0.365	0.563	-0.334	0.408	-0.307	0.813	0.806	0.893	1	-0.533	-0.001	0.736
RQ critic...	-0.097	0.183	-0.620	0.062	-0.203	-0.213	-0.430	0.279	-0.397	0.025	-0.744	-0.683	-0.682	-0.533	1	0.287	-0.807
RQ V0	0.148	0.285	-0.156	-0.110	-0.187	0.046	-0.123	0.018	-0.086	-0.034	-0.138	-0.061	-0.047	-0.001	0.287	1	-0.175
Success...	-0.026	-0.115	0.751	-0.230	0.304	0.332	0.611	-0.344	0.472	-0.183	0.874	0.822	0.876	0.736	-0.807	-0.175	1

Figure 2: Related correlation analysis of the most significant features

4. Development of artificial neural network models

We construct a computational process for constructing and studying ANN models to assess the accuracy of their training and classification. To do this, we use the Rapidminer system and blocks for importing a data set from a *.csv file, setting a target variable, and a subsystem for dividing the sample into test and validation. In order to conduct a systemic study and determine the ANN model type influence nature used on the final classification accuracy, assessed by different metrics, it is necessary to create several ANN models with different architectures. In this regard, we use 3 types of ANN models: single perceptron (SP), multilayer perceptron (MP) and deep multilayer neural network (DNN). The structure of the developed process for creating and modeling ANN operation is shown in the figure 3. All blocks are unitary commands aimed at processing data and performing processes for modeling the operation of ANN.

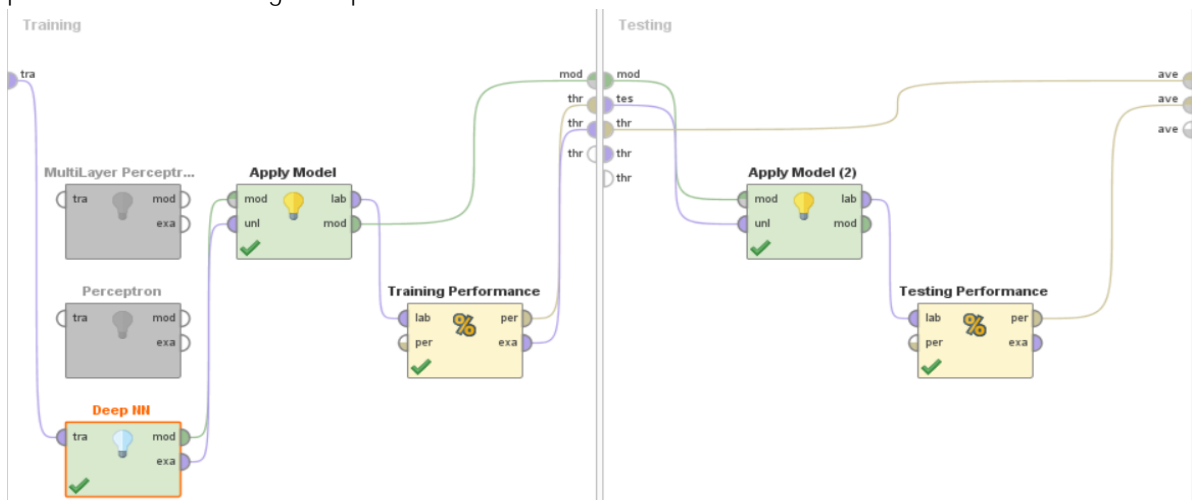


Figure 3: The structure of the developed process for creating and modeling the operation of an ANN
In general, the research pipeline is based on the following stages:

- importing the input data set using the Retrieve block, formatting and converting them to a unified form for subsequent training of ANN models;
- setting input and output features for training the model by using the Set Role block;

- creation of a Validation container for combining blocks for constructing ANN models for the purpose of carrying out training processes, testing and evaluating the accuracy metrics (Apply model and Performance blocks);
- ANN models research results export and visualization in tabular and graphical form.

Training and test data are divided among themselves in the proportion of 75% to 25%, respectively.

5. Experiments and results

10 computational experiments were carried out with different sets of parameters (hidden layers number, activation functions, learning rate coefficients, error rates). The average obtained metrics values for assessing model's accuracy are shown in the table below.

In particular, for a single perceptron, the value of the learning rate coefficient varied from 0.05 to 0.3. For a multilayer perceptron, 2 hidden layers of 5 and 3 neurons were created, respectively.

For the deep ANN, 50 hidden layers were created. The results of obtained ANN model's metrics evaluation to the first experiment are given in Table 1.

Table 1

The results of obtained ANN model's metrics evaluation to the first experiment

Metric name	Metric values of ANN models					
	Single Perceptron (SP)	Perceptron	Multilayer Perceptron (MP)	Perceptron	Deep NN (DNN)	
	Training set	Test sample	Training set	Test sample	Training set	Test sample
Accuracy	86.90%	83.72%	100.00%	95.35%	100.00%	97.67%
Classification error	13.10%	16.28%	0.00%	4.65%	0.00%	2.33%
Kappa	0.708	0.667	1.000	0.898	1.000	0.948
Weighted mean recall	85.11%	85.95%	100.00%	94.88%	100.00%	96.67%
Weighted mean precision	85.71%	82.83%	100.00%	94.88%	100.00%	98.28%
Spearman rho	0.708	0.667	1.000	0.898	1.000	0.949
Kendall tau	0.708	0.667	1.000	0.898	1.000	0.949
Absolute error	0.131 +/- 0.337	0.163 +/- 0.369	0.004 +/- 0.013	0.038 +/- 0.171	0.029 +/- 0.070	0.036 +/- 0.150
Relative error	13.10% +/- 33.73%	16.28% +/- 36.92%	0.37% +/- 1.33%	3.78% +/- 17.14%	2.85% +/- 6.99%	3.57% +/- 14.99%
Squared error	0.131 +/- 0.337	0.1628 +/- 36.92%	0.001 +/- 0.001	0.031 +/- 0.157	0.006 +/- 0.020	0.024 +/- 0.143
Corellation	0.708	0.667	1.000	0.898	1.000	0.949
Logistic loss	0.363	0.375	0.314	0.327	0,293	0,305

As we can see (Fig. 4), the least accurate classification results on both the training (about 84%) and training set were shown by the SP model (about 87%), which is due to its simplified architecture, the absence of all hidden layers and a general number of hyperparameters. affecting model's final accuracy.

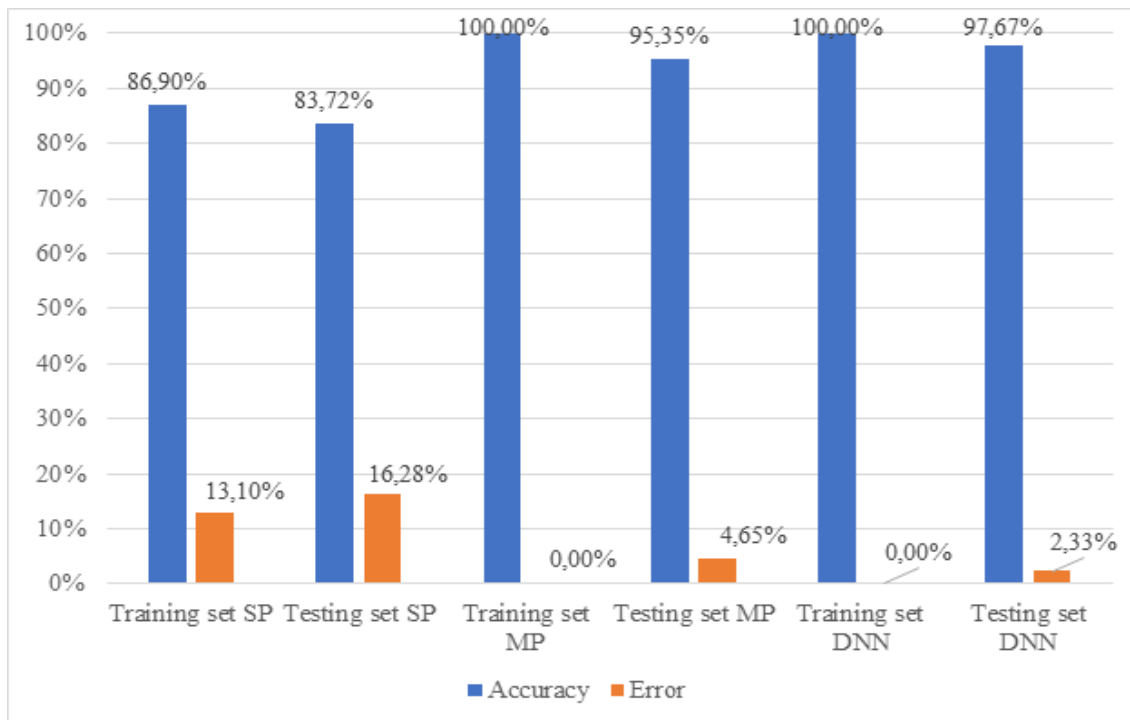


Figure 4: Visualization of the results of comparing estimates of accuracy and error metrics for the created ANN models of the first experiment

The MP and DNN models showed approximately the same results for metric evaluations on the training subset of data, however, the accuracy of DNN was 2.3% higher on the test subset, which may be due to a more complex model structure and a larger number of all performed computational iterations.

An additional experiment was aimed at reducing the dimension of input features. A unique identifier, calculated values of SIRI quartiles, SII, HbA1c, RQ quintiles, IOP V0 were used as input features; the output feature is "success of treatment".

Research modelling was performed on the created three ANN models with the same parameters. The results of evaluating the metrics of the obtained NN models for the second experiment are given in Table 2, Fig. 5.

In the third experiment, gender was excluded from the original sample. This reduces noise effects because this feature does not carry a significant semantic load in the context of data analysis.

The results of evaluation of the metrics of the obtained NN models for the third experiment are given in Table 3, Fig. 6.

As a result of ANN constructing significant input parameters were established that most influence the effectiveness of treatment: SIRI quartiles, SII, HbA1c and RQ quintiles. During inflammation, leukocytes accumulate in the lesion and the speed of local blood flow decreases. Impaired retinal microcirculation is observed in patients with type 2 diabetes mellitus (T2DM) without clinically significant diabetic retinopathy [17].

Table 2

Results of evaluation of metrics of the obtained ANN models for the second experiment

Metric name	Metric values of ANN models					
	Single Perceptron (SP)		Multilayer (MP)	Perceptron	Deep NN (DNN)	
	Training set	Test sample	Training set	Test sample	Training set	Test sample
Accuracy	86.90%	73.81%	100.00%	93.02%	100.00%	90.70%
Classification error	32.56%	26.19%	0.00%	6.98%	0.00%	9.30%
Kappa	0.355	0.487	1.000	0.822	1.000	0.769
Weighted mean recall	72.31%	80.42%	100.00%	90.05%	100.00%	88.44%
Weighted mean precision	67.97%	74.89%	100.00%	92.33%	100.00%	88.44%
Spearman rho	0.400	0.550	1.000	0.824	1.000	0.769
Kendall tau	0.400	0.550	1.000	0.824	1.000	0.769
Absolute error	0.326 +/- 0.469	0.262 +/- 0.440	0.009 +/- 0.017	0.049 +/- 0.153	0.029 +/- 0.070	0.112 +/- 0.21
Relative error	32.56% +/- 46.86%	26.19% +/- 43.97%	0.94% +/- 1.65%	4.91% +/- 15.26%	2.85% +/- 6.99%	11.18% +/- 21.13%
Squared error	0.326 +/- 0.469	0.262 +/- 0.440	0.001 +/- 0.000	0.026 +/- 0.094	0.006 +/- 0.020	0.057 +/- 0.163
Corellation	0.400	0.550	1.000	0.824	1.000	0.769
Logistic loss	0.437	0.413	0.316	0.329	0,293	0.349

Table 3

Results of evaluation of metrics of the obtained ANN models for the third experiment

Metric name	Metric values of ANN models					
	Single Perceptron (SP)		Multilayer (MP)	Perceptron	Single Perceptron (SP)	
	Training set	Metric name	Training set	Metric name	Training set	Metric name
Accuracy	89.29%	95.35%	100.00%	97.67%	98.81%	97.67%
Classification error	10.71%	4.65%	0.00%	2.33%	1.19%	2.33%
Kappa	0.769	0.898	1.000	0.948	0.974	0.948
Weighted mean recall	89.37%	94.88%	100.00%	96.67%	99.09%	96.67%

Weighted mean	87.74%	94.88%	100.00%	98.28%	98.33%	98.28%
precision						
Spearman rho	0.771	0.898	1.000	0.949	0.974	0.949
Kendall tau	0.771	0.898	1.000	0.949	0.974	0.949
Absolute error	0.107 +/- 0.309	0.047 +/- 0.211	0.005 +/- 0.016	0.024 +/- 0.151	0.034 +/- 0.101	0.037 +/- 0.147
Relative error	10.71% +/- 30.93%	4.65% +/- 21.06%	0.47% +/- 1.57%	2.39% +/- 15.06%	3.41% +/- 10.11%	3.70% +/- 14.69%
Squared error	0.107 +/- 0.309	0.047 +/- 0.211	0.000 +/- 0.001	0.023 +/- 0.151	0.011 +/- 0.058	0.023 +/- 0.140
Corellation	0.771	0.898	1.000	0.949	0.974	0.949
Logistic loss	0.354	0.331	0.315	0.322	0.324	0.326

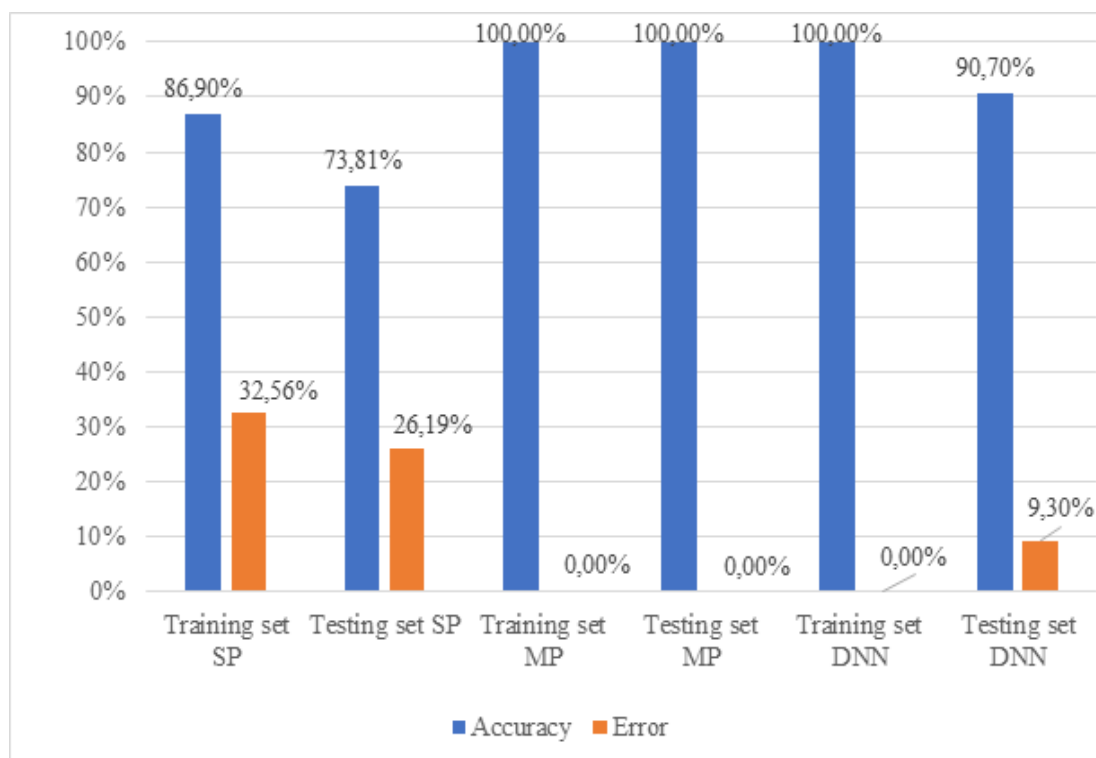


Figure 5: Visualization of the results of comparing estimates of accuracy and error metrics for the created ANN models for the second experiment

Altered blood flow in patients with type 2 diabetes contributes to macrovascular (peripheral vascular disease and coronary artery disease) and microvascular (diabetic retinopathy and diabetic nephropathy) complications. Our results confirm that higher values of S1R1, S1I, HbA1c and RQ indicate the severity of the disease and determine the need for diabetes mellitus stabilization [4], additional anti-inflammatory and anti-ischemic treatment in patients with painful NVG of diabetic origin to improve treatment prognosis.

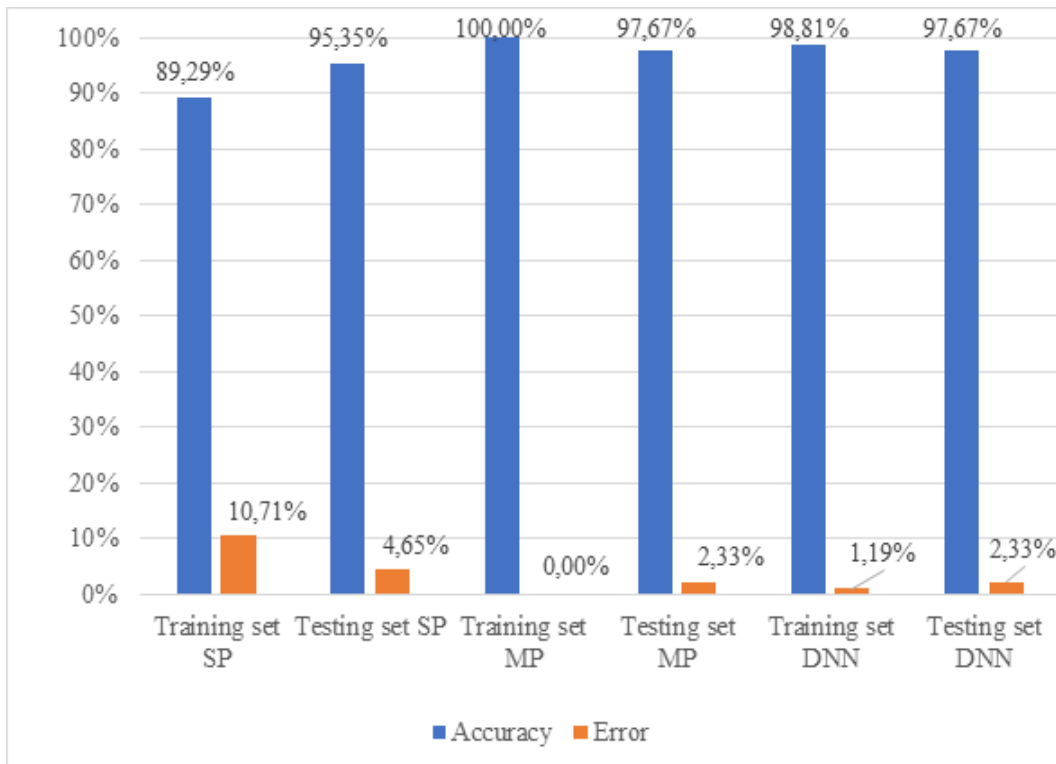


Figure 6: Visualization of the results of comparing estimates of accuracy and error metrics for the created ANN models for the second experiment

6. Conclusion

The conducted research made it possible to establish a higher adaptability of deep learning models, in particular deep fully connected ANN models, for the analyzed data set. The SP model demonstrates unstable accuracy on the training and test samples in different experiments, which may be due to shortcomings in determining the weight values of features at different iterations, as well as limitations in generalization ability. The MP model is more stable in all experiments, demonstrating high accuracy and completeness; its construction speed is 25% higher than the SP model. Presumably, the accuracy of this model can be increased through a more efficient organization model hyperparameter values automating selection process. The DNN model is the most accurate, but its training process is the most resource-intensive and takes almost 4 times longer than the SP model. A promising direction for further research is the search for optimizing the ANN training process in order to minimize training and testing errors, as well as increase the generalization ability of models in general.

It has been established that the most significant diagnostic features of the collected dataset in the context of the problems under consideration are the indicator of glycosylated hemoglobin HbA1c of the volumetric intraocular circulation (RO), the systemic inflammatory response index (SIRI) and the systemic inflammation index (SII). The data obtained allow us to conclude that the use of neural networks to predict the effectiveness of treatment is justified and timely. By taking into account and stabilizing blood sugar, as well as adjusting indicators of inflammation and microcirculation in patients with diabetic neovascular glaucoma, it is possible to ensure a timely significant reduction in intraocular pressure, maintain visual acuity, and therefore the quality of life of patients.

The data obtained allow us to conclude that the use of different ANN to predict the effectiveness of transcleral cyclophotocoagulation is justified. Timely prescribed treatment of identified changes in glycolized hemoglobin (HbA1c), volumetric intraocular circulation (RO), systemic inflammatory response index (SIRI) and systemic inflammation index (SII) against the background of transcleral cyclophotocoagulation can provide a significant reduction in intraocular pressure of at least 20%, maintaining visual acuity and patients life quality with painful diabetic neovascular glaucoma.

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