

Conference Paper

# Machine Learning Technologies and Psychological Testing of Pre-School and Primary School-Aged Children in Diagnostics of Perinatal Affection of the Central Nervous System

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## Abstract

The present study deals with computer-assisted learning technologies used for the analysis of psychological test results of children to diagnosis perinatal affection of the central nervous system. The mathematical models of logistic regression and gradient boosting give the best results within the accuracy of 81%.

**Keywords:** Machine learning, children, central nervous system, perinatal affection.

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Received: 25 July 2018

Accepted: 9 August 2018

Published: 1 November 2018

Publishing services provided by  
Knowledge E

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Selection and Peer-review under the responsibility of the Fifth International Luria Memorial Congress Conference Committee.

## 1. Introduction

Psychological testing of school children is necessary for diagnostic assessment of learning disability and mental impairment. Neuropsychological changes identified in children by means of qualitative and quantitative psychometric methods are often connected with perinatal affections of some areas of the child's brain occurred during pregnancy and labor. Hereditary changes of genes also play an important role in the abnormal development of child's mental activity [1]. In that context nowadays the problem of the influence of genetic factors and perinatal affection of the central nervous system on psychological and mental health of a child at different age is of current scientific interest [2]. Modern computer technologies enhance the solution capability of the above-mentioned problem [3].

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## 2. Methodology

The present study used data about the patients who had different clinical forms of perinatal affection of the central nervous system: hypoxic-ischemic central nervous system injury, hypoxic-hemorrhagic central nervous system injury, natal spinal cord injury, craniospinal injury. Further the children of different ages: pre-school (3-6 years), primary school-aged (7-11 years) were examined on a once-only basis. The study methods of neuropsychological status of pre-school and primary school-aged children were the following: audio-verbal and visual memory state, attention concentrating, exhaustion, compensatory ability, acoustic and visual gnosis, kinesthetic and constructional praxis, reading, calculation, writing, Q - intelligence. During the study we used words memorizing test, pattern recognition aptitude test, Sculte tables, speech understanding test, phonemic awareness test, Kohs Cubes test, WISC methods subtests, and other tests [4]. Each test was estimated on a scale from one to five. For the comparison study we used examination data about the children who had never had any perinatal affection of the central nervous system and lived at the same social conditions. The number of children in groups with perinatal affections of the central nervous system was 99 (in pre-school groups) and 141 in primary school-aged groups, while in the comparative groups the number of primary school-aged children was 133 and pre-school children -152. For classification we used the following mathematical methods of computer-assisted learning: support Vector Machine, logistic Regression, Random forest, gradient boosting, artificial neural networks. We did the data analysis with the help of the programming language Python. The library Scikit-learn was used for transformation of semantic features "gender" and "health problem" were transformed into "1" or "0". More that, data scale processing was carried out.

## 3. Results

At the beginning we did pretest data analysis. For quantitative evaluation of correlations between features we did correlation analysis. With the help of the library Pandas and function "corr" we got cross-correlation according to the results of psychological testing was 44 in junior age group and 65 in senior age group. The most important correlations for the junior age group were attention exhaustion, audio memory, compensation of attention deficit; for the senior age group - compensation of attention deficit, visual gnosis, IQ - test, visual memory and calculation. The data base was divided into training and testing groups-function train\_test\_split. The training of models

was carried out with the help of the function fit and the appropriate model, presented in the library SkLearn. With the help of the function GridSearchCV we selected optimal parameters for algorithm workflow. Table 1 shows the results of this selection.

TABLE 1: The main algorithm parameters and the range of their Optimization.

Model	Optimization parameters	Range of values
Support Vector Machine	C Gamma	0.001, 0.01, ..., 1000 Auto, RS
Logistic Regression	Penalty C	L1, L2 0.001, 0.01, ..., 100
Random forest	N_estimators Max_features	120, 300, 500, 800, 1200 Log2, sqrt, none
Gradient boosting	Gamma Max_depth	0.05, 0.1, 0.3, 0.5, 0.7, 0.9, 1.0 3, 5, 7, 9, 12, 15, 17, 25
Multilayer perceptron	Hidden_layer_sizes Activation	2... 150 identity, logistic, tanh, relu

For each model we plotted ROC-curves with AUC-evaluation, using the function ROC\_auc. To evaluate effectiveness of the model in the context of independent data array we used cross-validation method. The validity of each model was tested-cross\_val\_score. In the junior age group the gradient boosting model gave the best result - 0,66. In the senior age group the best result - 0,8- belonged to logistic regression and gradient boosting models. The results of the cross-validation test analysis showed the quality of classification of the gradient boosting model is higher than the one of the logistic regression model. To evaluate the performance quality of the models we used the following metrics: precision, recall, fl-score (Table 2).

TABLE 2: The results of model performance.

	3-6 years				7-11 years			
	precision	recall	f1-score	support	precision	recall	f1-score	support
0	0.58	0.74	0.65	34	0.64	0.83	0.73	35
1	0.67	0.50	0.57	36	0.81	0.61	0.69	41
total	0.63	0.61	0.61	70	0.73	0.71	0.71	76

To evaluate the quality of the models we used cross-check (Table 2).

TABLE 3: The results of cross-check.

3-6 years	7-11 years
0.676	0.773

Having compared the metrics: precision, recall, fl-score and the results of models cross-check we can make the following conclusions: the model of evaluation of perinatal affection of the central nervous system in primary school-aged children based on psychological testing gives the best results.

## 4. Discussion

Higher results of model performance in the senior age group occur due to more developed brain structure of the children. It gives opportunities to use additional testing methods- writing and reading.

## 5. Conclusions

The evaluation of the results of psychological testing of children by means of machine learning technologies allows diagnosing perinatal affections of the central nervous system and providing treatment and preventive care of diminution of cerebral competence.

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