Hamid Moghadasi[1], Reza Rabiei[2*], Fateme Kamyab Kalantari[3]
[1]Department of Health management and Information Technology, Faculty of Paramedical Sciences, Shahid Beheshti University of Medical Sciences, Tehran,Iran(moghaddasi@sbmu.ac.ir)
[2]Department of Health management and Information Technology, Faculty of Paramedical Sciences, Shahid Beheshti University of Medical Sciences, Tehran,Iran
[3]Department of Health management and Information Technology, Faculty of Paramedical Sciences, Shahid Beheshti University of Medical Sciences, Tehran,Iran(f.kamyab1717@gmail.com)
**corresponding Author: R.Rabiei@sbmu.ac.ir*

COMPARISON OF THE EFFICIENCY OF NEURAL NETWORK AND FUZZY NEURAL NETWORK MODELS IN AUTISM DISORDER PREVENTION

Abstract:
Background and purpose: *Autism spectrum disorders are one of the most commonly reported mental disorders and behaviors in children. Because of the complexity, the variability and similarity of the symptoms of this type of disorders with other developmental disorders, the diagnosis of autism is not easily possible. The present study was conducted to compare the efficiency of autistic prediction models based on the neural network of multilayer perceptron and fuzzy neural networks.*

Materials and Methods: *In this study, NDAR database was used for modelling. Initially, 34 risk factors were identified in the database by October 2010, from which 27 risk factors were extracted. The samples were between 4 and 11 years old. The pre-processing was performed using WEKA and SPSS23 software. The Toolbox of the MATLAB 2015 software version B was used for the preparation of the final models, and MedCale software was used to compare their curved surface.*

Results: *The highest performance with two hidden layers, 100 rounds, and 10 neurons in the secret layer was obtained using the LM algorithm in the multi-layer perceptron neural network model. The rates for sensitivity, specificity and accuracy of the ROC curves of this model were 96%, 98%, 97%, and 0.98 respectively. In the fuzzy neural network model (clustering model with overlapping radius of 0.8), the highest sensitivity, specificity, accuracy, and surface area under the ROC curve are 98%, 1, 99%, and 1.*

Conclusion: The identified risk factors considered in this study and multi-layer perceptron neural network and fuzzy neural networks could be useful for early diagnosis of autism disorder.

Keywords: *Autism Spectrum Disorders, Multilayer Perceptron, Neural Network, Fuzzy Neural Networks.*

Introduction:

Since mental disorders and behavior in society are increasing today (1), early diagnosis of these disorders plays an important role in reducing the high costs of the family and community (2).

Autism spectrum disorders are among the common mental disorders and behavior in children, (3).

Autism is a condition or impairment of central nervous system function, which results in insufficiency of the information reaching the brain; the outcome of such failure is a functional and behavioral disorder of the person with autism (4). In the fourth Diagnostic and Statistical Manual of Mental Disorders, a variety of autism spectrum disorders has been introduced as a subset of developmental disorders. Inclusive growth disorders include a group of mental disorders in which there is a disorder in social skills, behavior, and language development (5). Among all developmental disorders, autism has the highest prevalence and constitutes more than two thirds of these disorders (6).

According to the latest statistical data, the prevalence of autism is 5 times higher in boys than girls (7). Based on information from the Welfare Organization, there are about 5,000 autistic patients in Iran, and this number is rising.

Based on autism studies, several factors are involved in the incidence of this disease. The most important factors are stress and mother's concern during pregnancy (8), delivery by cesarean section (9), neurological problems and brain development abnormalities (7), history of social communication disorders in parents (10), genetic factors, during pregnancy problems, and after pregnancy problems (11).

Due to the complexity of the disease and variety and the closeness of the symptoms of this disorder with other developmental disorders, the diagnosis of autism is not easily possible (12). Currently, the diagnosis of autism is based on observable behaviors and there are no laboratory and definitive tests in this area. From the point of view of detection time, the best time to detect this disease is before 18 months (11). Early diagnosis of autism makes it possible to provide more appropriate treatment for this group of children (12).

Data mining techniques are widely used in health applications because of their predictive power in diseases. Hence, the existence of predictive systems for the diagnosis of people with the disease along with medical methods is necessary to reduce costs and medical errors and improve the quality of diagnosis (13).

Among these techniques, the neural network has been widely used in medicine as one of the most widely used predictive algorithms for artificial intelligence-based data modeling (14). Although the use of the neural network due to the high cost of the network training process, the high sensitivity of the parameters that determine the network architecture and the complexity of interpreting the results by the specialist have certain difficulties, but its ability to model the complex nonlinear has an advantage comparing to simpler data mining methods. In order to eliminate the limitations associated with neural network methods, the use of fuzzy neural networks has been considered in recent years (15).

The prediction of autism disorder using the multilayer perceptron neural network and fuzzy neural network can be effective in early diagnosis of the disorder and, subsequently, more efficient health care provision. Therefore, the aim of this study was to predict autism disorder using two techniques of multi-layer perceptron neural network and fuzzy neural network.

Materials and Methods:

At the outset, the identification of the risk factors for autism disorder was performed based on the latest sources and receiving professional opinions from experts. Risk factors were examined through a study of specialized texts and articles. A total of 34 risk factors were identified to predict autism disorder. After studying resources, new papers and experts' advices, the 27 risk factors that were mentioned in most texts were selected. Then prioritization of risk factors was performed using CART method using SPSS version 23 software. In Table (1), each factor, along with its importance, is observed in percentages. Subsequently, the creation of multi-layer perceptron neural network models and fuzzy neural model were studied.

Table 1. Risky factors at Autism disorder in order of priority

Risk factor	Importance (Percentage)
Type of marriage (familial, non-familial)	100
Communication and speech disorders background	100
Mother's stress and worries during pregnancy	100
Record of allergy in pregnancy	100
Hit to the baby's head	90
The age of parents increasing (father, mother)	80
Seizure	70
Fever	30
Delivery as cesarean section	11
Thyroid gland hypothyroidism at pregnancy	7
Medication use	6
Infant hypoxia at birth	5
High blood pressure	0.98
Infection during pregnancy	0.97
Abortions before 20 weeks	0.86
Radiology during pregnancy	0.81
Mother's diseases records	0.79
Mother's bleeding during pregnancy	0.75
CT scan during pregnancy	0.66
Abnormal weight at birth	0.63
Hit to the mother's belly	0.58
Record of childhood infectious diseases	0.58
Having Meningitis disorder	0.50
The size of the baby's head at birth (normal)	0.39
Jaundice at birth	0.32
Premature baby (length of pregnancy less than 37 weeks)	0.16
The parent's location change	0.15

Findings:

In the multi-layer perceptron neural network model, 70% of data was assigned to training, 15% to evaluation, and 15% to test data. In order to identify the number of nodes in each hidden layer, this number was changed from 5 to 100, and also the number of training cycles in the range of 90 to 1000, and various models of the neural network of the multi-layer perceptron were evaluated. The results of this assessment are presented in Table 2. The most efficient model (in terms of evaluation indicators) in the perceptron neural network with two hidden layers and the LM training algorithm has 10 neurons in the hidden layer. The optimal amount in the number of training cycles was 100. Sensitivity, specificity, accuracy, and surface area under the ROC curve were obtained at 96%, 98%, 97%, and 0.98, respectively, in the most efficient neural network model of laminated perceptron

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Table 2. Evaluation of different models of multi-layer perceptron neural network in test data

Model	Count of training cycles	The number of neurons in the hidden layer	Accuracy (Percentage)	Sensitivity (Percentage)	Specificity (Percentage)	AUC
1	1000	45	85.42	84.14	87.05	0.87
2	900	100	83.08	82.03	87.09	086
3	500	50	90.62	92.44	90.18	0.91
4	350	100	85.1	81.05	87.09	0.84
5	250	15	92.3	89.09	91.75	0.91
6	200	20	89.7	91.58	90.5	0.90
7	100	18	90.5	93.06	92.07	0.91
8	90	15	92.3	94.01	95.66	0.92
9	125	8	94.86	92.65	91.05	0.90
10	100	10	97.70	96.00	98.40	0.98

Subsequently, a fuzzy neural network was created using the MATLAB software ANFIS toolkit (a FIS primitive model using the GenFis2 function, the method for creating a fuzzy clustering system). 80% of the data was used for training and 20% of the data was for testing. In order to improve the selected model, the number of training periods, the incremental and decreasing rates of movement (steps), as well as the amount of overlapping clusters were evaluated. The results of this assessment are presented in Table 3. As can be seen in the table, the lowest average error for training and testing data is related to row 10, which is equal to 0.066 and 0.019 for training and test data, respectively. In the selected model, the overlap center is 0.89 with a sensitivity of 98%, a 100% specificity, a 99% accuracy, and a surface below curve of 1.

Table 3. The results of fuzzy neural network model evaluation in training data

Number of model	The amount of overlapping clusters centers	Count of training cycles	The reduction rate of steps	The increasing rate of steps	Average error rate	Total squared error
1	0.52	200	0.84	1.26	0.215	4.890
2	0.61	150	0.91	1.19	0.098	5.153
3	0.32	100	0.81	1.29	0.124	4.344
4	0.51	150	0.72	1.38	0.101	4.680
5	0.70	150	0.92	1.11	0.090	5.215
6	0.31	50	0.99	1.11	0.317	3.468
7	0.75	200	0.81	1.29	-0.086	4.356
8	0.80	100	0.82	1.28	-0.075	5.015
9	0.90	100	0.85	1.25	-0.074	4.223
10	0.89	100	0.93	1.17	0.066	4.999

Table 3. Results of evaluation of fuzzy neural network model in test data

Number of model	The amount of overlapping clusters centers	Count of training cycles	The reduction rate of steps	The increasing rate of steps	Average error rate	Total squared error
1	0.52	200	0.81	1.29	0.192	5.065
2	0.61	150	0.96	1.14	0.698	2.409
3	0.32	100	0.84	1.26	0.968	5.168
4	0.51	150	0.72	1.38	0.687	4.236
5	0.70	150	0.91	1.19	0.102	2.283
6	0.31	50	0.93	1.17	-0.287	0.961
7	0.75	200	0.84	1.26	0.198	0.019
8	0.80	100	0.85	1.25	-0.125	0.012
9	0.90	100	0.86	1.24	-0.200	0.008
10	0.89	100	0.91	1.19	0.019	2.409

In order to compare the significant difference, the sensitivity, specificity and accuracy of the two models derived from, statistic t and P-value were used. These indices were tested at the significant level of 0.05. Regarding the P-value obtained which are 0.275, 0.335, and 0.154, respectively (related to the indicators of accuracy, specificity and sensitivity). Since the P-value >0/05, there is no significant difference between sensitivity, specificity and accuracy in the three models of multi-layer perceptron neural network and fuzzy neural network in predicting autism disorder. These results are shown in Table 4.

Table 4. Comparison of the indicators of the accuracy, sensitivity and characteristics of the neural network, fuzzy neural network

Indicator	Test-Statistis t	P-Value	Description
Accuracy	1.484	0.275	No significant difference
Specificity	1.192	0.355	No significant difference
Sensitivity	2.241	0.154	No significant difference

The surface under the curve of the neural network model was tested with a sub-curve of the fuzzy neural model in order to differ in the significant level of 0.05. The value of P >0.05 was obtained. As shown in Table 5, the results indicate that the difference between the surface below the ROC curve in the neural network model of the multilayer perceptron and the fuzzy neural network is not meaningful. The unreasonableness of these indicators means that the use of tested models in the prediction of autism disorder is of equal importance (although the fuzzy neural network model is more efficient).

Table 5. The results of ROC sub surface test in fuzzy neural network and neural network models

Discussion:

In this study, the efficiency of multi-layer perceptron neural network models and neural fuzzy network for prediction of autism disorder was assessed based on the sensitivity, accuracy, and under-curve of the ROC. And the results were selected with higher sensitivity, specificity, accuracy, and surface area under the ROC curve.

In a similar study, Tamilarsy et al. (15) conducted a study entitled "Anticipating the severity of autism disorder using the fuzzy neural network" with 40 information records. After training and testing the data used in both of the post-propagation algorithms, the surface area of the ROC curve was calculated as 0.85%-0.90%. In the research carried out by the researcher, according to the use of fuzzy neural network model, the model has a higher efficiency (AUC = 1).

Yamini Chand conducted a study entitled "Comparison of the Effectiveness of Algorithms and Activation Functions in Neural Networks in Detection of the Severity of Autism Disorder" (16) with 416 records of information provided by NIMH.

In this study, 40 variables were considered. After reviewing different types of algorithms, (GDA, GDX, RP, CGF, CGP, CGB, SCG, BFG, LM), the LM algorithm had the highest performance.

Lowest value	0.9320
Highest value	1.0000
Arithmetic mean	0.9737
95% CI for the mean	0.8830 to 1.0643
Median	0.9890
Variance	0.001332
Standard deviation	0.03650
Standard error of the mean	0.02107

One sample t-test

Test value	1
Difference	-0.02633
95% CI	-0.1170 to 0.06434
Degrees of Freedom (DF)	2
Test statistic t	1.24957
Significance level	P = 0.3379

It was also shown in this study that increasing the number of hidden layer neurons does not necessarily have an effect on performance. The accuracy in this study for training, validation and test data are respectively: 0.99, 0.99 and 0.99%. On the other hand, in the research carried out by the researcher, similar results were obtained with the use of the LM algorithm and the failure to increase the number of neurons in improving the efficiency.

Conclusion:

Considering the use of artificial intelligence in recent years in the field of diagnosis and anticipation of diseases, this study can help promote and develop artificial intelligence in the field of health. By creating more effective medical decision-making systems, doctors and health care organizations benefit patients in the prognosis of the disease, as these systems bring about the speed and precision of decision-making, and this process can increase survival of patients. Among the research constraints, it can be noted that due to lack of access to information sources in the country, the data from the National Database for Autism Research was used in this study.

More expert physicians and access to internal data sources will result in higher performance models. Considering the results reached in this study with respect to the early diagnosis of autism disorder, it is hoped that by doing more research, these models can be used to help predict autism disorder in the health system. It is also suggested that future studies include Fuzzy C-Means and Swarm optimization to predict autism disorder.

Contribution of the authors:

Hamid Moghadasi: Designing the study and participating in preparing the manuscript; Reza Rabiei: Designing the study and finalizing the manuscript, Fatemeh Kamyab Kalantari: Reviewing the literature and facilitating access to the database.

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