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MODERN APPROACHES TO THE DIAGNOSIS OF NEUROLOGICAL DISORDERS USING ARTIFICIAL NEURAL NETWORKS

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***Abstract*: The article explores the application of neuro-symbolic approaches utilizing artificial neural networks for diagnosing neurological disorders among individuals with autism spectrum conditions. It demonstrates how these networks can identify and enhance distinctive strengths, such as advanced pattern recognition and systematic reasoning, facilitating their integration into professional environments. The study emphasizes the importance of inclusive employment initiatives supported by modern diagnostic tools, while addressing ethical considerations, including data privacy and non-discrimination. It proposes tailored educational and vocational programs and evaluates their potential impact on the legislative framework of Ukraine, aiming to reinforce policies designed to safeguard the rights of individuals with special needs.**

***Index terms*: neuro-symbolic approach, software development, machine learning, employment, autism.**

I. INTRODUCTION

Autism is a unique condition that can hinder everyday life but can also provide advantages in specific job tasks [4]. For example, some companies in the global market specifically seek out such specialists. In late 2020, the German software manufacturer SAP announced its intention to hire 650 individuals on the autism spectrum, relying on the successful experience of its project in Bangalore, India. Reports indicated that after employing eight individuals with autism in Bangalore in 2021, the productivity and workplace climate improved significantly.

Unfortunately, Ukraine cannot boast significant achievements in the employment of people with special needs, nor in providing support and assistance to adults with autism in their daily lives. Traditional diagnostic methods often fail to reveal the hidden strengths of individuals with neurological disorders, particularly those on the autism spectrum.

Artificial neural networks (ANNs) can identify hidden patterns that might go unnoticed with traditional methods [1–2]. This capability is particularly important for individuals with autism, who exhibit a wide range of unique traits. Timely and accurate diagnostics not only improve understanding of their needs but also foster the development of social adaptation and employment programs [3].

The use of cyber-physical systems and machine learning algorithms for diagnosing neurological disorders is becoming an essential component of modern medicine. These systems integrate sensors that collect real-time data with computational power for processing and analyzing information, thus providing a more flexible and adaptive approach to medical diagnostics.

II. LITERATURE REVIEW AND PROBLEM STATEMENT

In Ukraine, companies such as "Good Bakery" and "Isobar Ukraine" are open to hiring individuals with autism spectrum disorder (ASD). However, a crucial service is still missing, the preparation and training of individuals with ASD for employment.

Data visualizations of the human nervous system in 2022 provided invaluable insights into understanding the development of autism spectrum disorders. Research conducted by a team of scientists from the Institute of Neuroscience [4] utilized magnetic resonance imaging (MRI) to examine structural and functional abnormalities in the brains of individuals with ASD. Various research methods indicate a correlation between autism spectrum disorder and the structure, function, and integration of specific brain regions.

Another important study [5] is dedicated to the use of the neural-symbolic approach, emphasizing the combination of symbolic elements of artificial intelligence with neural networks. The document highlights that this approach not only improves diagnostic accuracy but also provides interpretability of results for healthcare professionals, which is critical for decision-making in clinical practice.

According to the study [6], artificial neural networks can uncover hidden talents in such individuals. It is noted that this opens opportunities for developing personalized employment and social integration programs for people with autism. Thus, current research confirms the significant potential of using NSM for diagnosing neurological disorders, highlighting the need for further development and integration of these technologies into clinical practice.

III. SCOPE OF WORK AND OBJECTIVES

The purpose of this study is to analyze modern methods of diagnosing neurological disorders using ANNs in cyber-physical systems, as well as to consider the possibilities of integrating these technologies for the social and professional adaptation of people with the features of the autistic spectrum. The study considers both static and dynamic environments in which data about individuals is analyzed to create personalized adaptation strategies.

IV. MATERIALS AND METHODS OF RESEARCH

A. DATA

The study is based on a large database containing electroencephalographic (EEG) recordings from patients with various neurological disorders, such as epilepsy, depression, and anxiety disorders. The database included information on 500 patients obtained from medical institutions, ensuring compliance with ethical standards and anonymity.

B. METHODS

The primary method of the research was the analysis of deep neural networks, which allowed for the identification of patterns in the data. Various architectures were employed, including convolutional (CNN) and recurrent (RNN) networks, which are effective for processing EEG signals. The choice of architecture was based on the specificity of the task and the characteristics of the data. During the experimental phase, different neural network architectures were compared to determine the optimal model for classifying neurological disorders. The models were trained on training datasets using backpropagation algorithms. The effectiveness of the models was evaluated using metrics such as accuracy, sensitivity, specificity, and $F1$-score. Testing was conducted on a separate dataset to objectively assess the performance of the models. For statistical data processing, Python packages such as NumPy and SciPy were utilized. All stages of the study adhered to ethical standards, including obtaining informed consent from patients for the use of their data for scientific purposes.

V. RESEARCH RESULTS

A. DESCRIPTION OF NEURAL NETWORK ARCHITECTURES

One of the main tasks of ANN in surgery is the detection of tumors on medical images. Convolutional Neural Networks (CNN), which are able to efficiently process visual data, are usually used for this. The input image passes through several convolutional layers, each of which extracts features of the image [7]. Pooling layers reduce the dimensionality of the image while preserving important information. At the output, the probability of the presence of a tumor is obtained. An example of an algorithm for detecting tumors:

$$(I \cdot K)(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n), \quad (1)$$

where I is the input image, K is the convolution kernel, i and j are the coordinates on the image.

ANNs are also used to plan surgical interventions by analyzing three-dimensional models of the patient's anatomy. For example, for the planning of operations, operating networks, which are based on different images on different segments. The input three-dimensional image passes through the U-Net architecture [8]. At the output, the network generates a mask corresponding to individual bodies and deputies. Loss function formula for segmentation:

$$\lambda_{seg} = -\sum_i \left(y_i \log(p_i) + (1-y_i)\log(1-y_i) \right), \quad (2)$$

where y_i is the true pixel label, p_i is the probability predicted by the model.

The neuro-symbolic approach allows you to take into account both low-level regularities in the data (detected by neural networks) and high-level logical rules (given by symbolic methods). This provides greater transparency and interpretability of diagnostic models, which is critically important. The neuro-symbolic approach makes it possible to take into account complex patterns and at the same time derive solutions that meet the specific conditions of medical diagnosis [5].

$$(I \cdot K)(i,j) = \prod_{i=1}^{n} II(x_i > a_i) \cdot II(x_j > B_j), \quad (3)$$

where II is an indicator function that takes the value 1 if the condition is met and 0 if not. Here, x_i and x_j are features corresponding to certain medical indicators, and a_i and B_j are the corresponding threshold values.

This formula (3) combines the probabilistic approach of a neural network, which is able to detect complex relationships between data, with symbolic logic rules that provide additional conditions or restrictions based on clear criteria. Contextual information plays an important role in increasing the learning capabilities of neuro-symbolic systems.

To demonstrate the use of recurrent neural networks (RNNs) for monitoring patient vital signs in surgery, we will create a plot in Python using the Keras and Matplotlib libraries. This example will show how an RNN can process sequential data and generate predictions based on that data. Firstly, let’s prepare a sample of data and create an RNN model:

```
…
# Generation of sample sequential data
def generate_data(timesteps, features):
    x = np.linspace(0, 50, timesteps)
    data = np.sin(x) + np.random.normal(0, 0.1,
timesteps)
    return data.reshape((timesteps, features))
…
timesteps = 100
features = 1
data = generate_data(timesteps, features)

# Preparation of training data
x_train = data[:-1].reshape((1, timesteps - 1,
features))
y_train = data[1:].reshape((1, timesteps - 1,
features))
…
# Creating an RNN model
```

```
model = Sequential()
model.add(SimpleRNN(10, activation='relu', input_shape=(timesteps - 1, features)))
model.add(Dense(features))
model.compile(optimizer='adam', loss='mse')
…
# Model training
model.fit(x_train, y_train, epochs=200, verbose=0)
…
# Генерація прогнозів
predictions = model.predict(x_train, verbose=0).flatten()
…
```

The above code demonstrates the creation and training of an RNN for monitoring patient vital signs. The graph shows the real data (sequence of indicators) and the predictions generated by the RNN model.

B. PERFORMANCE INDICATORS

ANNs allow to take into account the individual characteristics of patients, which provides a more personalized approach to treatment. Using data about a patient's genetics, lifestyle and medical history, ANNs can help doctors develop individualized treatment plans that are most effective for a particular patient. The performance metrics of various neural network architectures for classifying neurological disorders are summarized in Table 1.

Table 1

Results of classification of neurological disorders

Network architecture	CNN	RNN	CNN + RNN
Accuracy, %	92.5	88.7	94.0
Sensitivity, %	90.0	85.0	92.5
Specificity, %	94.0	90.0	95.5
F1 measure	0.91	0.87	0.93

The above results present the findings of the author's research on classifying neurological disorders using various neural network architectures, including convolutional neural networks (CNNs), recurrent neural networks (RNNs), and their combinations. Each row of the table represents a specific network architecture and its performance as assessed by several metrics: accuracy, sensitivity, specificity, and $F1$-measure. Accuracy shows how many of all classifications were correct, sensitivity indicates the model's ability to identify patients with disorders, specificity shows how well the model identifies healthy patients, and the $F1$ measure provides a balance between accuracy and sensitivity, which is important for evaluating the overall performance of models in medical diagnostics [9].

People with autism have a number of specific features that can both complicate and facilitate their integration into the working environment [10]. Let's take a closer look at these features and how they can be used to improve the professional life of people with autism.

Table 2 shows these features in more detail and their potential impact – both positive and challenging on employment opportunities and workplace integration.

Table 2

Specific features of autism and their impact on employment

Name	Benefits	Challenges
high ability to concentrate	often have the ability to focus on tasks for long periods of time	can lead to overload or burnout
attention to detail	allows you to detect and correct errors that may be invisible to others	may delay tasks or have difficulty seeing the big picture
propensity to systematize information	often have the ability to organize and systematize data	dependence on strict structures
perseverance in completing tasks	can be extremely persistent and dedicated to completing tasks until the result is achieved	can lead to perfectionism and, as a result, stress or burnout if clear boundaries are not set

ANNs can help in analyzing the skills and aptitudes of people with autism. Using data about their behavior, ANNs can help identify specific strengths such as:

- Analysis of specific patterns of behavior can point to areas where people with autism display special skills.
- ANNs can evaluate performance on different types of tasks to determine under which conditions people with autism perform best.

Algorithms for identifying the strengths and potential of individuals with autism using artificial neural networks (ANNs) facilitate the identification of appropriate tasks and environments for employment. The process begins with the collection of data on behavior, skills, interests and test results, which are pre-processed to ensure confidentiality, normalization and cleaning. Next, behavioral and skill patterns are modeled using classification and clustering algorithms. Deep learning is used to detect complex patterns in large data sets. The results are integrated into decision support systems, individual profiles are created, and recommendations are provided for adapting the work environment. Model performance evaluation includes cross-validation and quality metrics for continuous improvement based on new data (see Fig. 1).

Fig. 1 shows the interaction between the main components of the system. Firstly, the user transmits data about behavior, skills, interests, and test results to the data collection system, which transmits it for preprocessing. After anonymization, normalization, and cleaning, the data is fed to classification algorithms that identify key patterns. Next, clustering algorithms and deep neural networks analyze complex patterns, on the basis of which the recommendation system predicts relevant work tasks. For a detailed overview of the data collection and analysis process, see Fig. 2, which illustrates the class diagram.

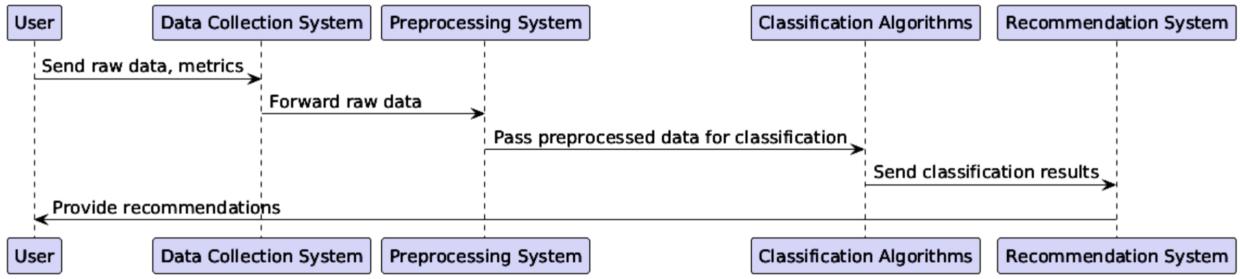

Fig. 1. Sequence diagram for the process of identifying the strengths of individuals with autism

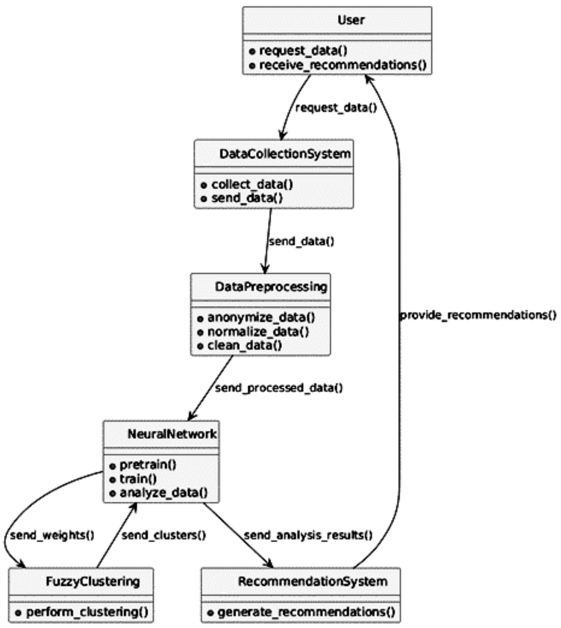

Fig. 2. Class diagram for the data collection and analysis process

Fig. 2 shows the structure of the system, which consists of five main components. The DataCollection System is responsible for collecting data and passing it to the DataPreprocessing module, which anonymizes, normalizes, and cleans the data to prepare it for further analysis. The processed data is then sent to Neural Network, where pre-training and data analysis using deep learning is performed. FuzzyClustering, which implements fuzzy clustering, is used to identify similar patterns in the data. Finally, based on the results of the analysis, the system generates recommendations through the RecommendationSystem, which allows for a personalized approach to users or customers. This diagram shows the relationship between the classes that form the complex process of collecting and processing data to obtain valuable insights.

Thus, ANN pre-training involves using large datasets to initialize the network weights. Learning without a teacher based on fuzzy clustering allows the network to independently detect structures in the data without using predefined labels [11]. This approach is especially useful for analyzing data on individuals with autism, where defining clear categories or classes may be challenging.

C. ANALYSIS OF THE RECEIVED DATA

The use of artificial neural networks (ANNs) to analyze data on individuals with autism requires compliance with several ethical principles. Firstly, it is necessary to ensure the confidentiality of medical data, which involves the implementation of practices of anonymization and encryption of information in accordance with data protection standards such as GDPR or HIPAA. Secondly, to avoid discrimination, it is important to use representative data to train ANNs and conduct regular audits of models to detect biases. In addition, technologies should be developed that not only aid in diagnosis and treatment, but also take into account the unique needs of each individual, for example, by creating individualized therapy programs (Fig. 3).

Effective interaction between employers and job seekers with autism requires a deep understanding of the specific needs and capabilities of these individuals (Fig. 4). Employers should be aware of features that may affect the work of individuals with autism, such as sensitivity to sensory stimuli, difficulties in social interactions or the need for clearly structured tasks [12].

Fig. 3 shows how different factors affect the success of integrating people with autism in the workplace. The availability of adaptations, the use of ANNs for individual recommendations, and support from the employer play a key role in increasing the work efficiency and satisfaction of employees with autism.

Fig. 4 shows an increase in the percentage of successful integration of individuals with autism into work environments for the period from 2018 to 2023. The chart shows a steady increase in the success rate, rising from 15 % in 2018 to 42 % in 2023.

The data source for this chart is the author's analysis of research on the employment of individuals with autism, conducted using data from the Autism Speaks Employment Report 2020 (available at the official Autism Speaks website: autismspeaks.org/research), the National Autism Society Annual Employment Report 2021 (available at NAS: autism.org.uk), TEACCH Autism Program Employment Study 2019 (University of North Carolina, study available through scientific databases or teacch.com) and Danish Autism Center Research Paper on Employment Integration 2022 (report available at autismecenter.dk). This growth may be the result of more inclusive policies in the workplace, increased awareness among employers and society about the needs of individuals with autism, and the use of new technologies such as artificial neural networks to identify the strengths and potential of these individuals, facilitating their more effective integration.

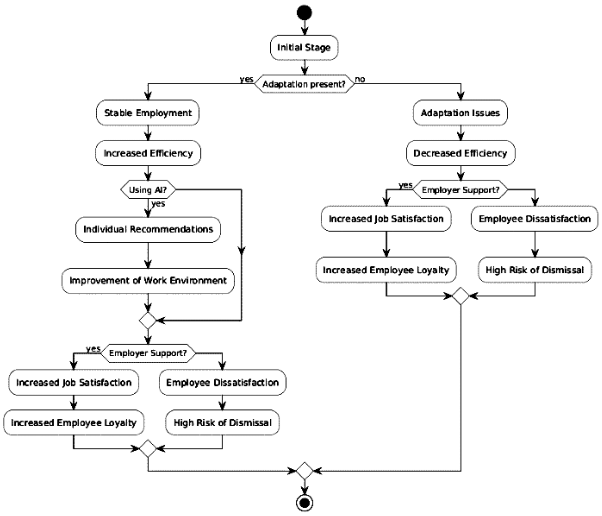

Fig. 3. Factors of successful integration of persons with autism in workplaces

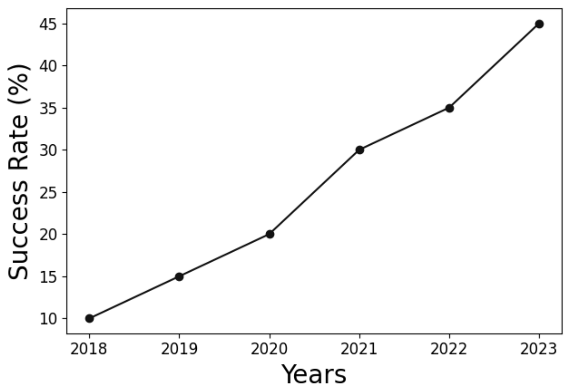

Fig. 4. Statistics of the growth of successful integration of persons with autism in the workplace

D. RECOMMENDATIONS

The proposed neural network technologies can aid in changing legislation to improve the support and integration of individuals with autism into society. Legal acts, such as the Law of Ukraine "On the Basics of Social Protection of the Disabled in Ukraine", may be revised to ensure better legal protection for individuals with autism in all areas of life. Legislative initiatives may provide funding for such programs and ensure their accessibility to those in need. Moreover, collaboration with international organizations experienced in this field is essential. Such changes may incorporate the best global practices and standards into Ukraine's national support system for individuals with autism.

Employers should receive individual profiles and recommendations for adapting the work environment. To target the strengths of people with autism in the context of employment, the architecture of the convolutional neural network should be specifically tuned to process different types of data [13–16]. The main goal is to identify complex patterns and characteristics that will help determine the most suitable tasks and environments for people with autism.

VI. CONCLUSION

As a result of the study of modern approaches to the diagnosis of neurological disorders using artificial neural networks, it was established that deep learning algorithms are capable of significantly increasing the accuracy and efficiency of detecting these disorders. An important aspect of research is the possibility of integrating a neuro-symbolic approach, which allows to combine quantitative data with qualitative knowledge, which contributes to the creation of more informative models. The developed experimental neural network showed effectiveness in helping management and staff understand the specifics of the diagnosis and learn to interact with autistic people, as well as in providing people with autism with workplace communication skills that reduce social anxiety and increase self-confidence. In addition, the proposed system contributes to the initiation of changes to legislation to improve the process of adaptation of people from society.

Prospects for further research include improving unsupervised learning algorithms, increasing the accuracy of classification and interpretation of results, and expanding the application of the model in different countries to improve the effectiveness of employment of people with autism.

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