A Multimodal Data Driven Rehabilitation Strategy Auxiliary Feedback Method: A Case Study

Lei Zhao, Haoran Sun, Fei Yang, Zilin Wang, Yufei Zhao, Weizhong Tang, and Lingguo Bu

***Abstract*— In Industry 4.0, medical data present a trend of multisource development. However, in complex information networks, an information gap often exists in data exchange between doctors and patients. In the case of diseases with complex manifestations, doctors often perform qualitative analysis, which is macroscopic and fuzzy, to present treatment recommendations for patients. Improving the reliability of data acquisition and maximizing the potential of data, require attention. To solve these problems, a multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed. In this study, depth sensor and functional near-infrared spectroscopy (fNIRS) were used to obtain ethology and brain function data, and skeleton tracking analysis and ethology discrete statistics were performed to assist the diagnostic feedback of rehabilitation strategies. This study takes rhythm rehabilitation training of autistic children as a case, and results show that the multimodal data-driven rehabilitation strategy auxiliary feedback method can provide effective feedback for individuals or groups. The proposed auxiliary decision method increases the dimension of data analysis and improves the reliability of analysis. Through discrete statistical results, the potential of data are maximized, thereby assisting the proposed rehabilitation strategy diagnostic feedback.**

***Index Terms*— Auxiliary decision, feedback, multimodal data driven, skeleton tracking.**

I. Introduction

IN INDUSTRY 4.0, information industry has achieved great development [1], [2]. Internet, artificial intelligence, big data, and other next-generation information technologies have entered a golden age of development. Industrial Internet is the product of Internet technology and the new generation of industrial revolution. This technology aims to break original technical barriers, improve the intelligence level of industrial equipment through technical integration, and establish an exchange platform between data and entities to improve the level of data analysis [3]. The emergence of industrial Internet promotes the integration and innovation of technology and influences the original industrial development model. This phenomenon is especially evident in the medical field.

The development of information industry promotes the emergence of a new generation of medical industry revolution called Medical 4.0. The goal of Medical 4.0 is to improve and integrate the new generation of information industry with the existing technology and equipment and for Medical 4.0 to be applied to medical care and diagnostic decision making [4]. Methods, such as telemedicine assistance and artificial intelligence, also begin to be applied in medical-assisted decision making. Although the importance of data has been fully recognized [5], an information gap still exists in data exchange between doctors and patients. Maximizing the use of these multisource data in complex information networks and realizing the potential of data for their application in rehabilitation strategy-assisted diagnostic feedback remain a challenge.

Statistics reveal that 12 million people in the United States are troubled by inaccurate medical diagnosis annually, and approximately 44,000 to 98,000 people die due to medical diagnostic errors [6]. The causes of inaccurate diagnostic results are diverse, but they can be divided into the following categories: one cause is artificial misdiagnosis brought about by the subjective qualitative analysis of doctors. Another cause is the lack of reliable medical testing technology, which creates obstacles in data and information exchange between doctors and patients [7], [8].

The combination of artificial intelligence and medical field has also been one of the research hotspots in recent years [9]. Statistics show that the market scale of medical artificial intelligence will reach 36.1 billion US dollars by 2025 [10]. Several studies have applied artificial intelligence methods to auxiliary diagnosis in recent years. This application improves intelligent processing methods in the medical field [11], [12]. However, in the case of complex manifestations of diseases, artificial intelligence often cannot consider the patient's condition; thus, artificial intelligence cannot effectively contribute to the patient's rehabilitation.

The development of Industry 4.0 has brought several positive changes to the medical industry. However, maximizing multisource and isomerized data, realizing their data potential,

Manuscript received December 27, 2021; revised March 25, 2022 and April 15, 2022; accepted April 25, 2022. Date of publication April 28, 2022; date of current version May 9, 2022. This work was supported in part by the Doctoral Foundation of Shandong Jianzhu University, China, under Grant X18039Z; in part by the Natural Science Foundations of Shandong Province, China, under Grant ZR2021QE115 and Grant ZR2020QE299; and in part by the Program of Qilu Young Scholar, Shandong University. *(Corresponding authors: Lei Zhao; Lingguo Bu.)*

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Digital Object Identifier 10.1109/TNSRE.2022.3170943

and applying them to rehabilitation strategy-assisted diagnosis feedback still require research. Combined with this description, the challenges in the medical field are as follows:

(1) In the face of neurologic diseases with complex manifestations, qualitative analysis methods often have macroscopic limitations. As a result, specific individual rehabilitation strategies are difficult to propose. Therefore, quantitative input feedback is necessary while improving the analysis method.

(2) The environment and use conditions often lead to the loss of effective information, and even affect the authenticity of data due to the limitation of the technical characteristics of some equipment, leading to the information gap between doctors and patients. Therefore, the improvement of data reliability is worth studying.

(3) Artificial intelligence methods have achieved good results in the diagnosis of various diseases, but limited by the data scale, they are often unable to form rehabilitation feedback for some complex neurological diseases. Therefore, effectively tapping the potential of data is also one of the main challenges at present.

In view of these challenges, a multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed. This method is intended to promote data exchange between doctors and patients through the integration of wearable devices and information-based methods and to aid decision making in rehabilitation through quantitative analysis. Ethology and biomarker information acquisition is completed using depth sensor and functional near-infrared spectroscopy (fNIRS). Discrete statistical analysis was performed on the obtained ethology data, and brain science analysis was combined with discrete statistical analysis to form feedback to assist the decision-making process in the rehabilitation strategy. The present study proposes an effective rehabilitation assistance strategy feedback through case analysis of rhythm rehabilitation training of autistic children. Case analysis results prove the feasibility of this system method.

The main contributions of this study are as follows: 1) a multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed to overcome the subjectivity of rehabilitation evaluation through quantitative analysis; 2) multimodal data collection is carried out through Kinect and fNIRS to improve the dimension of data analysis and increase the reliability of rehabilitation diagnosis; 3) statistical analysis to establish multidimensional data between the connection is conducive to the performance of complex neurological disorders to develop more targeted rehabilitation strategies; 4) the case of rhythm rehabilitation training of autistic children is illustrated and provides support for potential intervention age and more targeted rehabilitation training methods.

The remainder of the article is presented as follows: The second part introduces several related studies on data evaluation techniques and auxiliary diagnosis methods. The third part presents the overall system analysis framework. The fourth part shows the feasibility of the system method through a case study. The fifth part discusses the analysis results. The sixth part summarizes the article. The seventh part elaborates about research gaps and potential studies in the future.

II. Related Works

In Industry 4.0, medical data forms and auxiliary diagnostic methods show a diversified development trend. The related literature work presented in this paper mainly focuses on data evaluation methods and auxiliary diagnostic methods.

A. Data Evaluation Methods

Researchers have focused on maximizing the application of various methods to obtain patient information. Existing disease evaluation technology and data acquisition methods for patients show a diversified trend. Mainstream traditional evaluation methods include medical scale evaluation and clinical observation. Currently, numerous clinical evaluation methods are used mainly through the feedback of scale scores to measure the prevalence of the disease. Movement assessment battery for children-2, which measures the ability of autistic children to exercise based on assessment scores, is one of the most widely used autism exercise assessment scales [13], [14]. In COVID-19 studies, researchers also assessed possible sleep disorders using a scale. The method used multiple scales to evaluate the sleep disorders and mental states of medical staff [15]. Most evaluation results are completed by the qualitative analysis of doctors. However, scale evaluation methods and clinical observation are vulnerable to the influence of evaluators. Moreover, several studies have shown that the scale score may be affected by multiple factors, such as gender and social cognition. Among them, gender difference is considered one of the most important factors. Some female patients often disguise their social disorder, and then the situation of "scale camouflage" occurs. Therefore, the reliability of the scale score still needs to be improved [16]–[18].

Locating biomarkers through technical methods appears to be a more scientific approach than subjective evaluation. fNIRS is a portable brain function monitoring device. In recent years, numerous researchers have used wearable device to monitor people with cognitive impairment [19], [20]. Several researchers have also applied fNIRS to the detection of various biomarkers in sport tasks because of this device's portability [21], [22]. Electroencephalogram (EEG) is a method used to detect brain function through electrical signals. EEG is widely used in clinics because its data acquisition process is simple. This method is often combined with deep learning methods for disease classification and analysis [23]–[25]. However, EEG signals are easily affected by other signals. Another problem is that in terms of spatial resolution, electrodes can collect signals from the brain's surface, but determining whether the electrical signal is generated in the cerebral cortex or deeper areas is impossible. Functional magnetic resonance imaging (fMRI) technology is also one of the data acquisition methods widely used by researchers. This method forms an image of the changes in blood dynamics by neurons through magnetic resonance. However, the purchase price and annual maintenance cost of fMRI equipment are high; thus, it is unsustainable for several areas with underdeveloped medical conditions. The more complicated situation lies in the data. After analyzing volumes of fMRI data, Eklund *et al.* proposed that fMRI has a high probability of false positives in brain activity analysis.

Their study presents doubts about the reliability of fMRI research results [8], [26].

The importance of data in Industry 4.0 has been fully recognized. However, ensuring that the reliability of data overcomes subjectivity is the ground for eliminating information communication barriers between doctors and patients. Current data requirements are difficult to satisfy by only using a single data acquisition method. This approach requires to carry out the conduct of additional technology fusion and matching and fully realize the potential of data. Reliable data are transformed and applied to the auxiliary diagnostic feedback of rehabilitation strategy.

B. Auxiliary Diagnostic Method

The value of data has become increasingly evident in the era of rapidly developing Industry 4.0 [27], [28]. Data-driven methods make bridging the information gap between doctors and patients possible. The development of medical equipment promotes the generation of diversified medical data and presents new challenges to the traditional medical industry. With the integration of information technology and traditional medical equipment, these diversified data and information technology have derived several auxiliary diagnostic methods.

Telemedicine-aided diagnosis is one of the products of Industry 4.0. The potential of telemedicine has been increasingly evident during the COVID-19 pandemic. Telemedicine-assisted diagnosis of infectious diseases can communicate information in a more timely and convenient manner and reduce the consumption of medical resources [29]. Telemedicine-assisted diagnosis relies on the development of the information industry. Video or voice is used as the medium between doctors and patients. It significantly improves the convenience of the medical process and reduces medical cost. However, doctors are still the main body of telemedicine-assisted diagnosis, and the diagnosis is completed by their qualitative analysis. This approach is still subjective.

Compared with the diagnostic method of qualitative analysis, some healthcare workers extract patients' biomarkers to serve as the basis of auxiliary diagnosis. This method combines quantitative and qualitative analyses to extract biomarkers with the help of medical equipment. In recent years, researchers have widely applied fNIRS to several special populations with neurodevelopmental disorders [30], [31]. In the context of COVID-19, the rapid diagnosis of the patient's condition is critical to reducing the spread of the pandemic. Yong *et al.* explored the potential of antibodies as an auxiliary diagnostic biomarker of COVID-19. Studies show that antibody detection is an effective complement to the two diagnoses of suspected cases [32]. Although this method eliminates the influence of subjectivity, several biomarkers are sometimes contaminated due to the limitations of collection equipment or the environment. This limitation leads to the loss of effective information and even affects the reliability of the biological indicators collected. This auxiliary diagnostic method combining quantitative and qualitative analyses is one of the most widely used methods in medicine.

Artificial intelligence technology has attracted considerable attention because of its low cost and high expansibility. In the past, artificial intelligence has been widely used by researchers in target detection and cost evaluation [33], [34]. The combination of artificial intelligence and medical diagnosis has also been one of the research hotspots in recent years. Some researchers use neural networks to train multimodal neural networks to simulate the clinical diagnosis process of Alzheimer's disease, thereby improving the accuracy of auxiliary diagnosis while comprehensively analyzing patients' pathology and psychology. At the same time, with the development of Industry 4.0, the use of the Internet of things for real-time monitoring of medical data is one of the research hotspots [35], [36]. Several researchers directly used biomarkers as the input in models to diagnose diseases directly [37], [38]. Numerous achievements have been made in disease classification and learning through the machine learning method. However, this method is limited by the scale of medical data sets. Numerous diseases with complex phenotypes cannot be reliably diagnosed using this method. Another problem is that medical artificial intelligence focuses on prediction results. Studies on effective rehabilitation strategy feedback are limited.

The related literature reveals that auxiliary diagnostic methods have achieved significant progress in the past. The development of these auxiliary diagnostic methods has reduced the data gap between doctors and patients to a certain extent and contributed to the progress of the medical industry. However, several problems still need to be addressed. For example, telemedicine methods are primarily used to eliminate the data exchange gap in space but has not truly overcome the subjectivity of several evaluation methods. Determining how reliable information can be obtained is the key to using biomarkers as auxiliary diagnostic criteria. However, the data acquisition methods are often subject to technical or environmental constraints, resulting in the loss of information. The integration of artificial intelligence and traditional medicine has considerable potential, but most existing studies focus on the use of biomarker input for diagnosis and prediction. This method has not formed effective strategic feedback for several complex rehabilitation diseases.

C. Research Gap

Medical data and auxiliary diagnostic methods show a diversified development trend with science and technology development. However, in the data interaction between doctors and patients, the subjectivity of evaluating individuals or the reliability of the data itself still needs to be considered. In artificial intelligence-assisted diagnosis, the potential of some data still needs to be further tapped, and additional effective rehabilitation strategy feedback needs to be developed for several complex diseases. To address these challenges, a multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed. This method uses fNIRS with simple cost and strong anti-interference ability to monitor brain function and a depth sensor to track the bone. Compared with traditional methods, this research method increases the analysis dimension of data, has better stability during usage, and improves

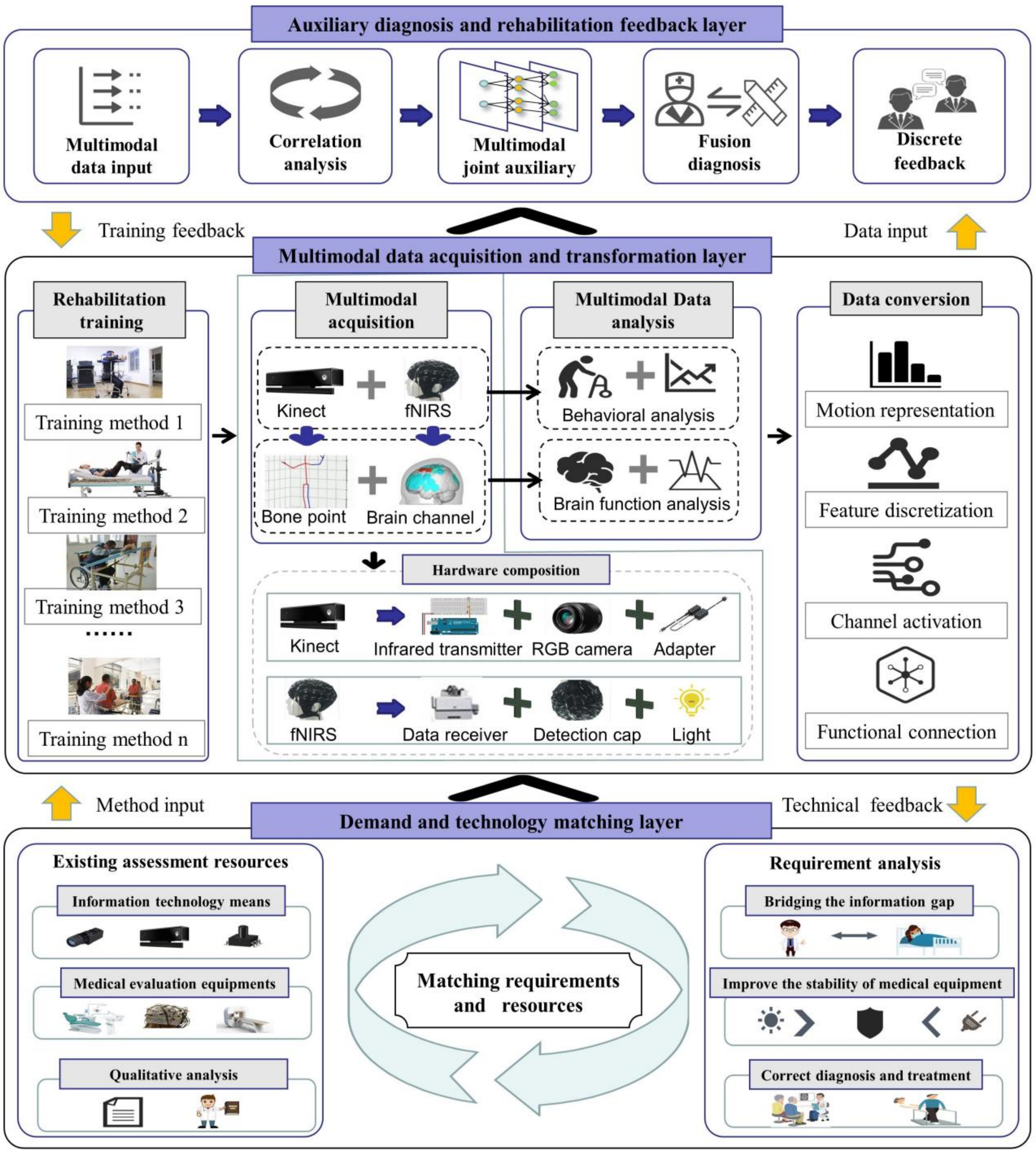

Fig. 1. Overall system framework. The system method framework includes the main implementation process and research methods.

data reliability. Discrete statistical analysis of ethology data can develop a more-targeted rehabilitation strategy to assist diagnostic feedback. This hybrid analysis and ethology-driven feedback method can be effectively applied to rehabilitation strategy-aided decision making.

III. Overall Architecture of the Proposed Framework

On the basis of these related studies, a multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed. As shown in Fig. 1, the system method framework includes the main implementation process and research method.

A. Demand and Technology Matching Layer

Industry 4.0 has driven the blowout development of information technologies. Sensors, deep learning, and other data acquisition and analysis methods bring new vitality into the medical industry. However, satisfying data requirements by using only one technical method is difficult.

Technology matching and multidimensional analysis are necessary to compensate for the limitations of single data while focusing on the needs of doctors and patients for multiple data.

The existing data collection methods are matched with information technology to form a reliable multidimensional auxiliary diagnostic tool and better serve the patient's rehabilitation process.

B. Multimodal Data Acquisition and Transformation Layer

On the basis of demand analysis and technology matching, the rehabilitation training method suitable for patients was selected, and the data were collected and analyzed by the multimodal method. Ethology and brain function data were acquired by Microsoft Kinect and fNIRS, respectively. They have the characteristics of high stability and strong anti-interference ability.

Multidimensional data analysis was mainly completed by motor representation and statistical data analysis. Ethology analysis mainly used the skeleton tracking to represent the patient's movement process, and brain function was mainly monitored by channel activation status. Correlation analysis method was used to establish the relationship between patients' ethology and brain function changes. Through correlation analysis, difference analysis, and other statistical methods to conduct multidimensional data analysis and quantification of behavioral and brain functions, the quantitative output results serve as auxiliary diagnostic standards.

C. Auxiliary Diagnosis and Rehabilitation Feedback Layer

In this section, the patient's rehabilitation process is feedback through quantitative and qualitative analyses. The quantitative analysis is mainly completed by the auxiliary decision process, which is actually an interrelated ethology and statistical analysis process of brain function. The first layer of auxiliary decision is mainly used to receive multidimensional patient data collected. At the second level, the quantitative input data of ethology and brain function are counted through correlation analysis and difference analysis, and the possible relationship between multidimensional data is established through data analysis. Brain science mainly focuses on analyzing differences between groups. Finally, based on the analysis results, the conclusion supporting the rehabilitation strategy auxiliary diagnostic feedback is drawn; it can be used to assist the analysis of complex performance among different individuals or groups.

The results of auxiliary analysis serve as an important basis for doctors' qualitative analysis, and the combination of quantitative analysis and qualitative analysis becomes more targeted in the formulation or improvement of interventional treatment plans.

IV. Case Study

The manifestations of several diseases may change with age. The development principle of these complex diseases is worthy of research. Mastering the high incidence range of several manifestations and carrying out targeted intervention treatment are critical to the future rehabilitation track of a disease.

A multimodal data-driven rehabilitation strategy-assisted diagnostic feedback method that can be used to analyze possible complex manifestations of patients with autism spectrum disorder (ASD) through ethology and brain science is proposed. This study takes rhythm rehabilitation training of autistic children as a case, and the results reveal that ethological differences and channel activation of brain function in autistic children may be related to age. This conclusion may support the age range of interventional therapy. Discrete statistics of ethology is also vital to the formulation of rehabilitation strategies.

TABLE I
Participant Group Characteristics

characteristics	Low age group	High age group
Sex(girl:boy)	2:8	1:9
Mean age(months)	52.8±9.0	73.8±8.0
Height(cm)	102.0±5.0	116.0±7.0
Weight(kg)	16.0±2.0	23.5±3.3
Score of ABC	32.2±1.9	30.8±0.8

A. Demand and Technology Matching

ASD is one of the most common neurodevelopmental disorders, with extensive and complex manifestations in behavior and neural function [39]–[41]. The traditional evaluation scheme lacks reliability and cannot form effective feedback on the rehabilitation of patients. Therefore, Kinect and fNIRS should be used to increase the data dimension.

Studies have proven that the overall impact of early intervention on social interaction results is significant, and the impact is the most significant at the age of 3.81 [42]. Therefore, this study takes preschool autistic patients as subjects and age as grouping characteristics. In the rehabilitation training program, the rhythm training program is matched with high participation of children, and the multidimensional monitoring conditions are satisfied. Twenty autistic children aged three to seven participated in the study through the local autistic children's rehabilitation center, where the diagnosis of autistic children was carried out by professional doctors. The children and their guardians were formally notified and approved before participating in the study. The characteristics of participant group are shown in TABLE I.

B. Multimodal Data Acquisition and Transformation Layer

Research has shown that ASD patients have atypical sensory perception and motor skills. The research on sensory motor abilities, such as auditory motor integration, is critical to the rehabilitation of patients [43], [44]. Therefore, rhythm training method was selected for this case study to complete the data collection.

Before a task, a trainer trained the subjects on the performance of a rhythm task for a similar duration. The rhythm task consisted of two different music rhythms, each of which was played in four cycles. The duration of the entire task was seven minutes. The first four minutes were the playback time of the first music rhythm. The last three minutes were the second stage. The entire test included the music rhythm of the entire body, and all subjects completed in a fixed position. During the task, the subjects had to wear a portable 46-channel near-infrared device. It was supported by Danyang Huichuang

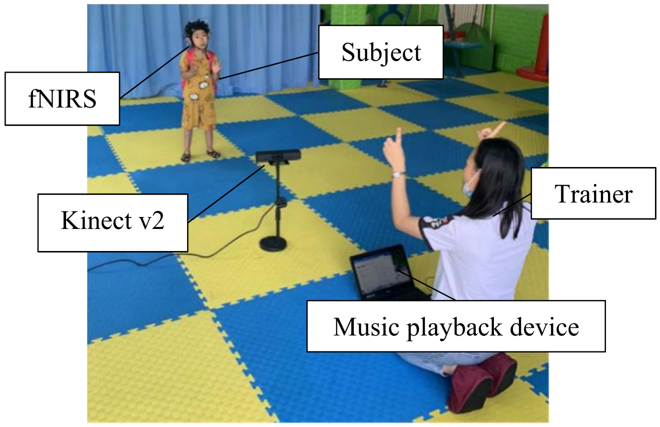

Fig. 2. Motion capture scene.

Fig. 3. Display of bone point effect during collection.

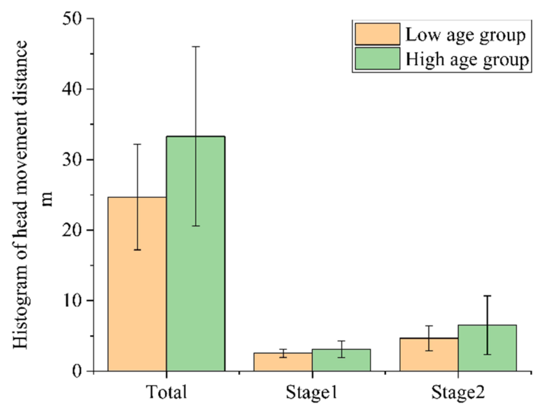

Fig. 4. Histogram of head movement distance in different stages.

Medical Equipment Co., Ltd. The sampling frequency is 10 Hz, and the wavelength is 750 and 850 nm. The device is composed of 24 signal sources and 16 detectors. Channels 1–6, 10–12, 16, 17, and 22 are distributed in the left prefrontal cortex (LPFC), channels 23–25, 30–32, 38–40, and 42–44 are distributed in the right prefrontal cortex (RPFC), channels 7, 8, 13, 14, and 18–21 are distributed in the left motor cortex (LMC), channels 26–29, 33, 34, 36, and 37 are distributed in the left motor cortex (RMC), channels 9, 15, and 45 are distributed in the left occipital lobe (LOL), and channels 35, 41, and 46 are distributed in the right occipital lobe (ROL).

The processing of fNIRS data includes screening and removing abnormal fragments and artifact signals, filtering out noise and interference signals, converting optical density into blood oxygen concentration according to hemodynamic response, taking 0–100 s as block param and −2–0 s as baseline. Finally, the transformed HBO and HBr signals are obtained.

The movement was recorded using a depth sensor placed between the trainer and the tested patient. The position of the visual sensor was parallel to the ground (i.e., approximately 0.6-m high) and placed in front of the participants at a distance of 1.5 m. At the beginning of the training task, the trainer plays the music.

The built-in skeleton tracking system of Kinect V2 can use the generated depth image to identify the human body, and the 3D information of 25 bone points of the human body can be generated by outputting the corresponding pixel values, as shown in Fig. 3.

The 3D position information in the entire video stream can be expressed as $[s_1, s_2 \ldots\ldots s_n]$. Each element in the list is represented as the input information of the corresponding frame. The video is decomposed into pictures frame by frame, and each picture shall contain 3D position information of 25 points $[(x_1, y_1, z_1), (x_2, y_2, z_2) \ldots\ldots (x_{24}, y_{24}, z_{24}), (x_{25}, y_{25}, z_{25})]$. The storage time of each frame of the picture is also written with the progress of the video stream, corresponding to the picture writing order as $[t_1, t_2 \ldots\ldots t_k]$.

The writing time t of each frame in the video corresponds to the 3D position input of the bone point one by one. By comparing the changes in the position information of the corresponding skeleton point, the motion speed υ_{in} of the corresponding bone point can be obtained as follows:

$$\upsilon_n = \sqrt{\left(\frac{x_n - x_{n-1}}{t_n}\right)^2 + \left(\frac{y_n - y_{n-1}}{t_n}\right)^2 + \left(\frac{z_n - z_{n-1}}{t_n}\right)^2} \tag{1}$$

Thus, the velocity of each bone point in the corresponding frame can be obtained as $(\upsilon_{i1}, \upsilon_{i2} \ldots\ldots \upsilon_{i25})$. The entire motion function is represented by υ.

$$\upsilon = \frac{\sum_{n=1}^{25} \upsilon_{in}}{25} \tag{2}$$

Therefore, the change process of the overall movement speed of autistic patients during the collection process is $(\upsilon_1, \upsilon_2 \ldots\ldots \upsilon_k)$. The change in acceleration $(a_1, a_2 \ldots\ldots a_k)$ can be obtained from the following speed change:

$$a = \frac{\upsilon_k - \upsilon_{k-1}}{t_k} \tag{3}$$

Clinicians have long been concerned about atypical head movements in autistic patients. In a comparative test, researchers conducted a comparative study between autistic and non-autistic patients, monitored the two groups of patients through non-invasive methods, and discovered typical differences in head movement between autistic and non-autistic patients [45]. The Kinect device was used to monitor the head's motion, extract the head feature points, analyze the

TABLE II
COMPARISON OF GROUP MOTION CHARACTERISTICS

	Low age group						High age group					
	Mean value			Std			Mean value			Std		
features	Total	Stg1	Stg2	Total	Stg1	Stg2	Total	Stg1	Stg2	Total	Stg1	Stg2
S_h	24.68	2.54	4.66	7.47	0.57	1.78	33.30	3.10	6.52	12.70	1.20	4.16
V	0.37	0.34	0.38	0.05	0.04	0.09	0.54	0.49	0.59	0.11	0.10	0.15
V_{std}	0.35	0.34	0.33	0.05	0.05	0.07	0.54	0.51	0.50	0.11	0.13	0.10
A	17.13	17.21	16.00	2.43	2.42	3.36	22.04	22.05	21.13	2.93	3.29	4.26
A_{std}	20.00	19.96	16.60	3.20	3.70	3.34	26.17	26.58	21.25	5.82	5.82	4.94

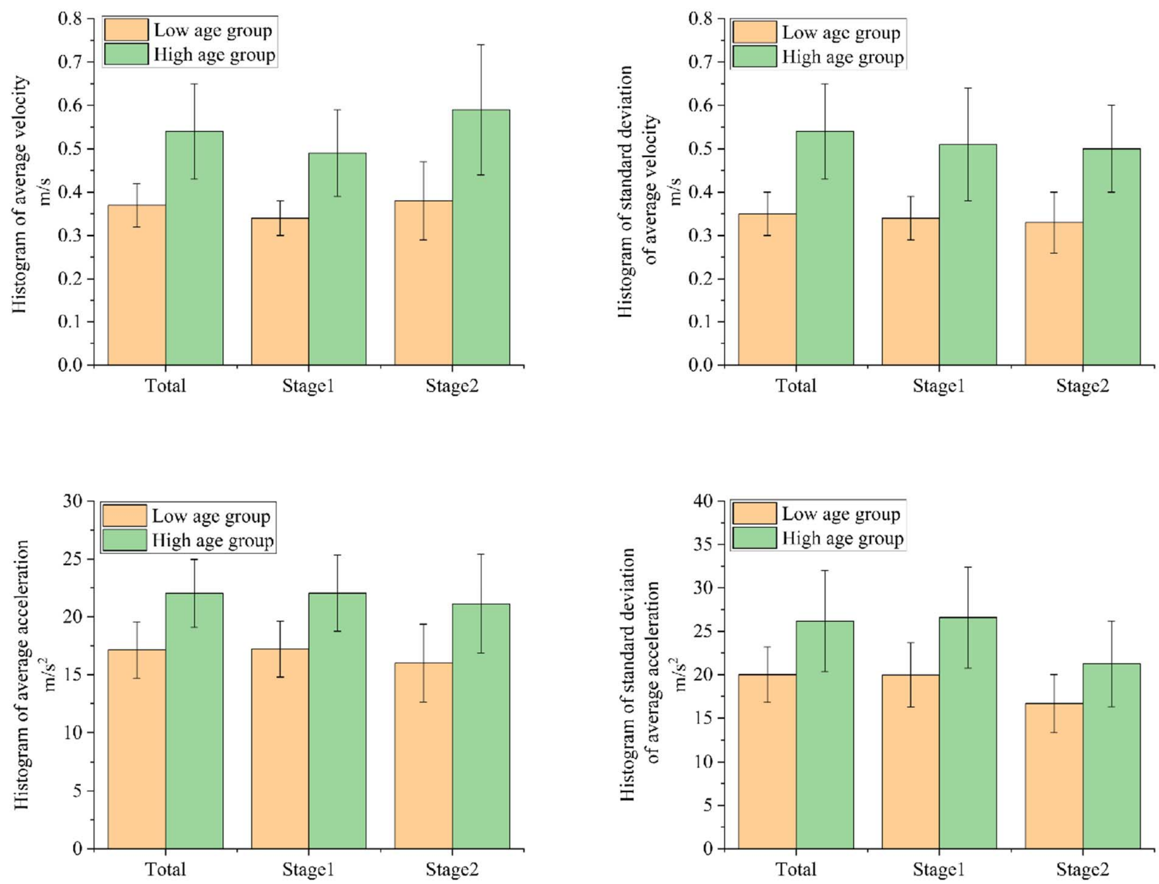

Fig. 5. Histogram of motion characteristics in different stages.

movement distance of the head, and consider one of the motion features.

$$s_h = \sum_{i=1}^{k} \sqrt{\left(x_{i3} - x_{(i-1)3}\right)^2 + \left(y_{i3} - y_{(i-1)3}\right)^2 + \left(z_{i3} - z_{(i-1)3}\right)^2} \tag{4}$$

The participants were screened during the experiment. The elimination is mainly due to the human interference in the data collection process and the low participation of participants, resulting in the data time less than 450s. Children who could not complete the research task were excluded in the research analysis. All samples of autistic children were divided into the following two groups: 3–5 years old and 5–7 years old. Finally, the sample data of 12 autistic children were retained, where numbers 1–6 represent the low age group and numbers 7–12 represent the high age group. In accordance with the similarities in motion, the motion features per minute in the first and the second motion stages were extracted and compared with the motion features of the entire process. The results of motion characteristic analysis are shown in the TABLE II.

The movement speed and acceleration can most intuitively reflect the movement ability. Head movement is also an atypical sign of ASD patients. The standard deviation of motion characteristics between the same groups can effectively measure the dispersion of data in the groups. By comparing the motion characteristics of the three stages, several rules can

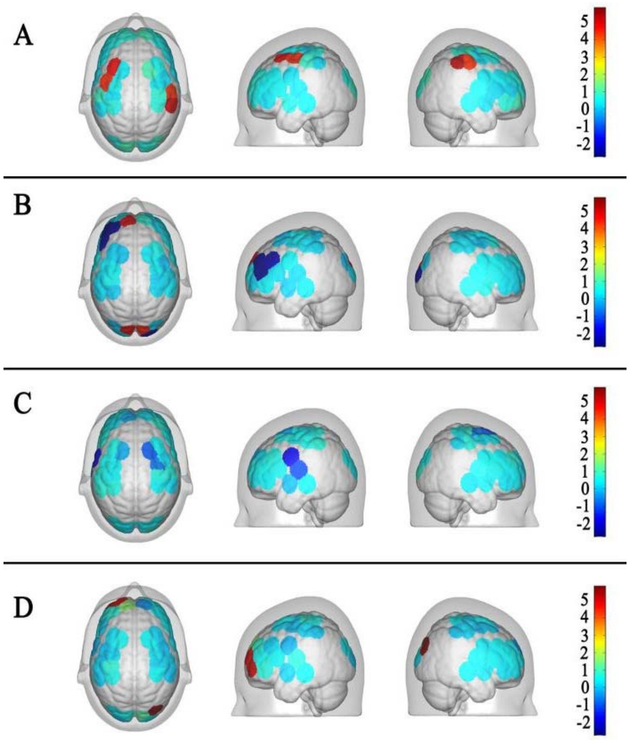

Fig. 6. Visualization results of brain function differences.

be found in the motion performance of the two data groups. The visualization results of several typical motion signs are shown in Figs. 4 and 5.

The visualization results of rhythm task analysis of autistic children through wearable fNIRS device are shown in Fig. 6. In the figure, *A* represents low-age movement state, *B* represents low-age rest state, *C* represents high-age movement state, and *D* represents high-age rest state.

T-test was used to analyze the channel activation in the resting state and rhythmic task state of the two groups, and a significant difference in Channel 11 in the lower age group ($t = 2.765$, $p = 0.040$) and Channel 1 in the higher age group ($t = 2.772$, $p = 0.039$) was observed. Comparing low-age tasks with high-age tasks, differences in Channels 1 ($t = 0.035$, $p = -2.865$), 9 ($t = 0.023$, $p = -3.234$), 11 ($t = 0.034$, $p = -2.904$), 12 ($t = 0.032$, $p = -2.934$), and 16 ($t = 0.031$, $p = -2.969$) were observed. The difference in rhythmic task state was significantly improved.

Differences were observed in LOL ($t = -3.386$, $p = 0.020$) and ROL ($t = -3.001$, $p = 0.030$). At rest, significant differences were observed in RPFC–LPFC ($r = 0.865$, $p = 0.026$) and LMC–RMC ($r = 0.993$, $p < 0.001$) in the low-age group. In the task state of the low-age group, the analysis results were LMC-ROL ($r = 0.827$, $p = 0.042$) and LOL–ROL ($r = 0.961$, $p = 0.002$). In the resting state of the high-age group, the analysis results were LPFC–RPFC ($r = 0.846$, $p = 0.034$), LPFC–RMC ($r = 0.944$, $p = 0.005$), LPFC–LOL ($r = 0.955$, $p = 0.003$), RPFC–LMC ($r = 0.865$, $p = 0.026$), RPFC–RMC ($r = 0.871$, $p = 0.024$), RPFC–LOL ($r = 0.904$, $p = 0.013$), and RMC–LOL ($r = 0.936$, $p = 0.006$). In the task state of the high-age group, the analysis results were LPFC–LOL ($r = 0.825$, $p = 0.043$) and LMC–LOL ($r = 0.948$, $p = 0.004$).

Pearson correlation analysis was conducted between the LOL, ROL, LPFC, RPFC, LMC, and RMC and the main motion indexes, such as head motion distance, mean velocity, standard deviation of velocity, mean acceleration, and standard deviation of acceleration. The results showed that the head motion distance ($r = 0.814$, $p = 0.048$), average velocity ($r = 0.834$, $p = 0.039$), velocity standard deviation ($r = 0.837$, $p = 0.038$), average acceleration ($r = 0.820$, $p = 0.046$), and acceleration standard deviation ($r = 0.820$, $p = 0.046$) in the lower age group was significantly correlated with the LPFC in the overall exercise assessment.

The mean velocity ($r = -0.915$, $p = 0.010$), standard deviation of velocity ($r = -0.854$, $p = 0.031$), and mean acceleration ($r = -0.851$, $p = 0.032$) were correlated with LMC in the second motion stage analysis of high age groups. Only the average velocity ($r = -0.817$, $p = 0.047$) was associated with LOL in the first motion stage analysis. Compared with the low age group, the correlation between brain activation and exercise in the high age group is more discrete, and it is more evident in the second stage of exercise.

C. Auxiliary Diagnosis and Rehabilitation Feedback Layer

The ethology analysis results reveal that the motor ability of the high-age group is higher than that of the low-age group, and no evident stagnation due to the influence of autism is observed. The dispersion of motion characteristics in the high-age group was significantly higher than that in the low-age group. This result shows that as age increases, the patients' motion stability becomes increasingly unstable. Analysis of the brain functions between the resting state and task state reveals significant differences in the activation of brain function channels between the two groups.

As shown in Fig. 7, these results were inputted as the first layer of the auxiliary diagnosis layer. In the second layer, the differences in ethology and brain function were analyzed. Several children with abnormal behavior were observed through discrete observation. The analysis of intergroup differences in brain function and behavior coincided, thereby supporting the possible influence of grouping characteristics. Therefore, the feedback results are summarized as follows: (1) the motor-level differentiation among members of the high-age group is evident; (2) significant differences were observed in motor differentiation and activation of brain functional channels between the two groups.

V. Discussion

With the advent of the information age, information-based methods improve the medical experience and diagnostic effect of patients. More data provide further possibilities for bridging the information gap between doctors and patients. However, with the increasing demand, data-driven auxiliary diagnosis methods still face multisource and isomerization challenges. This paper presents a multimodal data-driven rehabilitation strategy auxiliary feedback method. This method combines

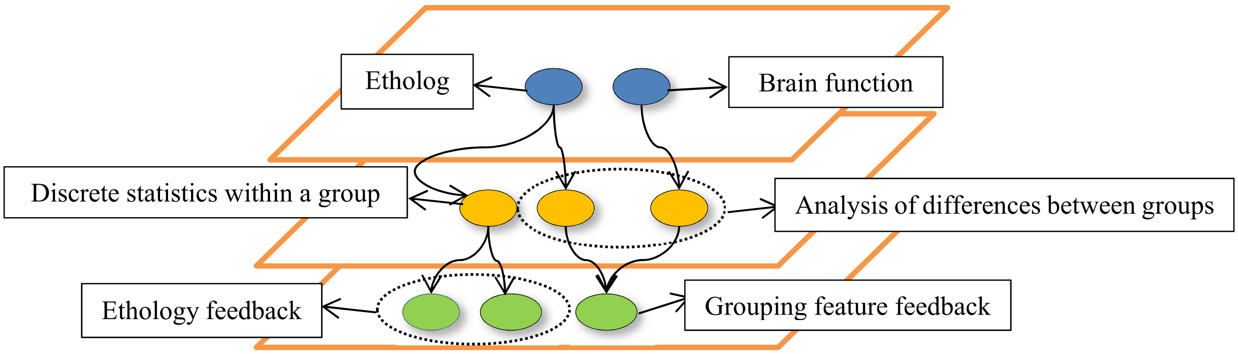

Fig. 7. Auxiliary decision process.

behavior and brain function for multidimensional quantitative analysis, increases the analysis dimension of data, and improves data reliability. The potential of data is tapped by means of statistical analysis, and the data output is applied as the basis of auxiliary diagnosis to the rehabilitation strategy feedback of patients.

This method has the following advantages when used. The depth sensor and fNIRS equipment have simple structures, stable signal acquisition process, less interference from external signals, and are highly convenient to use. The acquisition of brain and ethology signals is less limited by the scene due to the wearability of fNIRS and the high expansibility of the depth sensor. Thus, satisfying the needs of patients and doctors becomes easier. At the same time, multidimensional data are analyzed independently, and these data are used as the input of the auxiliary diagnosis hybrid decision-making process.

In the case study of autistic children, results have shown that children in the low-age group have higher performance in the correlation between exercise and brain activation than those in the high-age group. This finding is consistent with the direction of exercise performance and may be helpful to the study of autistic intervention age. At the same time, the activation of the high-age group in the post exercise stage is evident. It can also form a more targeted feedback on the subsequent rehabilitation. In this manner, an effective rehabilitation strategy feedback can be provided to patient groups or individuals. Data exchange between doctors and patients can also be promoted while providing medical innovation.

VI. Conclusion

The medical industry and information data are inseparable in Industry 4.0. Nevertheless, ensuring the reliability of data in complex data networks as much as possible to satisfy the usage requirements of patients and doctors is equally important. Reliable data sources guarantee accurate auxiliary diagnosis. Fully tapping the potential of data in auxiliary diagnosis can evaluate and provide feedback on the current state of patients. This process is highly important to the rehabilitation of patients. Thus, a multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed. The case of rhythm rehabilitation training of autistic children is illustrated to verify the effectiveness of the design methodology. The case study shows that this method is effective in rehabilitation strategy auxiliary diagnosis.

A multimodal data-driven rehabilitation strategy auxiliary feedback method is proposed. Taking the rhythm rehabilitation training of autistic children as an example, the effectiveness of this design method is verified by the joint detection of Kinect and fNIRS. The results show that the multimodal data-driven rehabilitation strategy auxiliary feedback method is effective. It forms more targeted attention to some cases with abnormal behavior. This condition is conducive to the subsequent rehabilitation and improvement, as well as the feedback on the intervention age of groups with neurodevelopmental disorders, such as autism. Our findings may help to form a multidimensional evaluation and feedback mechanism for a series of neurological disorders with complex manifestations and provide new ideas for targeted rehabilitation of patients in real life.

VII. Limitation and Future Works

Although this study can participate in the formation of rehabilitation strategy-assisted diagnostic feedback, it still has some limitations. For example, due to limited conditions, less sample data are available in this experiment. Although the small sample data do not affect the feasibility verification of the system research method, they may lack the support of large data sets in the feedback results. Establishing an effective link between brain science and behavioral data is also a potential work. In the future, more experiments should be added to verify the accuracy of the feedback results. At the same time, with the expansion of the sample size, an ethology and brain science database of ASD in different age groups should be established. Combined with the method of machine learning, we can consider behavioral features and brain function features as data input. Automatic identification and feedback of ASD can be achieved through a specific task.

References

[1] E. Islas-Cota, J. O. Gutierrez-Garcia, C. O. Acosta, and L.-F. Rodríguez, "A systematic review of intelligent assistants," *Future Gener. Comput. Syst.*, vol. 128, pp. 45–62, Mar. 2022.

[2] L. Bu, C.-H. Chen, G. Zhang, B. Liu, G. Dong, and X. Yuan, "A hybrid intelligence approach for sustainable service innovation of smart and connected product: A case study," *Adv. Eng. Informat.*, vol. 46, Oct. 2020, Art. no. 101163.

[3] W. Qin, S. Chen, and M. Peng, "Recent advances in industrial internet: Insights and challenges," *Digit. Commun. Netw.*, vol. 6, no. 1, pp. 1–13, Feb. 2020.

[4] A. Haleem and M. Javaid, "Medical 4.0 and its role in healthcare during COVID-19 pandemic: A review," *J. Ind. Integr. Manage.*, vol. 5, no. 4, pp. 531–545, Dec. 2020.

[5] S. M. Hosni, S. B. Borgheai, J. McLinden, and Y. Shahriari, "An fNIRS-based motor imagery BCI for ALS: A subject-specific data-driven approach," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 12, pp. 3063–3073, Dec. 2020.

[6] L. T. Kohn, J. M. Corrigan, and M. S. Donaldson, "Institute of medicine to err is human: Building a safer health system," *Annales Francaises D, Anesthesie Reanimation*, vol. 7, pp. 245–246, Dec. 2000.

[7] S. Tian, W. Yang, J. M. L. Grange, P. Wang, W. Huang, and Z. Ye, "Smart healthcare: Making medical care more intelligent," *Global Health J.*, vol. 3, no. 3, pp. 62–65, Sep. 2019.

[8] A. Eklund, T. E. Nichols, and H. Knutsson, "Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates," *Proc. Nat. Acad. Sci. USA*, vol. 113, no. 28, pp. 7900–7905, Jul. 2016.

[9] H. Zhang, Y. Guo, and D. Zanotto, "Accurate ambulatory gait analysis in walking and running using machine learning models," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 1, pp. 191–202, Dec. 2020.

[10] J. Lagasse, "Healthcare AI market expected to surge from \$2.1 to \$36.1 billion by 2025," in *Healthcare Finance*. Dec. 27, 2018. [Online]. Available: https://www.healthcarefinancenews.com/news/healthcare-ai-market-expected-surge-21-361-billion-2025.

[11] E. Eldele *et al.*, "An attention-based deep learning approach for sleep stage classification with single-channel EEG," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 29, pp. 809–818, 2021.

[12] M. Abdel-Basset and M. Mohamed, "A novel and powerful framework based on neutrosophic sets to aid patients with cancer," *Future Gener. Comput. Syst.*, vol. 120, no. 3, p. 125, Jul. 2021.

[13] S. E. Henderson, D. A. Sugden, and A. L. Barnett, *Movement Asessment Battery for Children*. London, U.K.: Harcourt Assessment, 2007.

[14] G. van der Veer, E. Kamphorst, A. Minnaert, M. Cantell, T. H. Kakebeeke, and S. Houwen, "Assessing motor performance in preschool children: The Zurich neuromotor assessment-2 and the movement assessment battery for children-2," *Perceptual Motor Skills*, vol. 128, no. 5, pp.-2014–2032, 2021.

[15] J. Qi *et al.*, "The evaluation of sleep disturbances for Chinese frontline medical workers under the outbreak of COVID-19," *Sleep Med.*, vol. 72, pp. 1–4, Aug. 2020.

[16] L. Hull *et al.*, "Gender differences in self-reported camouflaging in autistic and non-autistic adults," *Autism*, vol. 24, no. 2, pp. 352–363, Feb. 2020.

[17] R. K. Schuck, R. E. Flores, and L. K. Fung, "Brief report: Sex/Gender differences in symptomology and camouflaging in adults with autism spectrum disorder," *J. Autism Develop. Disorders*, vol. 49, no. 6, pp. 2597–2604, Jun. 2019.

[18] M.-C. Lai *et al.*, "Neural self-representation in autistic women and association with 'compensatory camouflaging,'" *Autism*, vol. 23, no. 5, pp. 1210–1223, Jul. 2019.

[19] L. Bu, C. Huo, Y. Qin, G. Xu, Y. Wang, and Z. Li, "Effective connectivity in subjects with mild cognitive impairment as assessed using functional near-infrared spectroscopy," *Amer. J. Phys. Med. Rehabil.*, vol. 98, no. 6, pp. 438–445, 2019.

[20] D. Yang, K.-S. Hong, S.-H. Yoo, and C.-S. Kim, "Evaluation of neural degeneration biomarkers in the prefrontal cortex for early identification of patients with mild cognitive impairment: An fNIRS study," *Frontiers Hum. Neurosci.*, vol. 13, p. 317, Sep. 2019.

[21] F. Herold, P. Wiegel, F. Scholkmann, A. Thiers, D. Hamacher, and L. Schega, "Functional near-infrared spectroscopy in movement science: A systematic review on cortical activity in postural and walking tasks," *Neurophotonics*, vol. 4, no. 4, Aug. 2017, Art. no. 041403.

[22] L. Bu, D. Wang, C. Huo, G. Xu, Z. Li, and J. Li, "Effects of poor sleep quality on brain functional connectivity revealed by wavelet-based coherence analysis using NIRS methods in elderly subjects," *Neurosci. Lett.*, vol. 668, pp. 108–114, Mar. 2018.

[23] X. Tang, W. Li, X. Li, W. Ma, and X. Dang, "Motor imagery EEG recognition based on conditional optimization empirical mode decomposition and multi-scale convolutional neural network," *Expert Syst. Appl.*, vol. 149, Jul. 2020, Art. no. 113285.

[24] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. S. Hossain, "Deep learning for EEG motor imagery classification based on multi-layer CNNs feature fusion," *Future Gener. Comput. Syst.*, vol. 101, pp. 542–554, Dec. 2019.

[25] C. Ieracitano, N. Mammone, A. Hussain, and F. C. Morabito, "A novel multi-modal machine learning based approach for automatic classification of EEG recordings in dementia," *Neural Netw.*, vol. 123, pp. 176–190, Mar. 2020.

[26] D. Kessler, M. Angstadt, and C. S. Sripada, "Reevaluating 'cluster failure' in fMRI using nonparametric control of the false discovery rate," *Proc. Nat. Acad. Sci. USA*, vol. 114, no. 17, pp. E3372–E3373, 2017.

[27] R. Huang, M. Liu, and Y. Ding, "Spatial-temporal distribution of COVID-19 in China and its prediction: A data-driven modeling analysis," *J. Infection Developing Countries*, vol. 14, no. 3, pp. 246–253, Mar. 2020.

[28] M.-L. Tseng, T. P. T. Tran, H. M. Ha, T.-D. Bui, and M. K. Lim, "Sustainable industrial and operation engineering trends and challenges toward Industry 4.0: A data driven analysis," *J. Ind. Prod. Eng.*, vol. 38, no. 8, pp. 581–598, 2021.

[29] B. Calton, N. Abedini, and M. Fratkin, "Telemedicine in the time of coronavirus," *J. Pain Symptom Manage.*, vol. 60, no. 1, pp. e12–e14, Jul. 2020.

[30] F. Zhang and H. Roeyers, "Exploring brain functions in autism spectrum disorder: A systematic review on functional near-infrared spectroscopy (fNIRS) studies," *Int. J. Psychophysiol.*, vol. 137, pp. 41–53, Mar. 2019.

[31] M. Abtahi *et al.*, "Merging fNIRS-EEG brain monitoring and body motion capture to distinguish Parkinsons disease," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 28, no. 6, pp. 1246–1253, Jun. 2020.

[32] G. Yong *et al.*, "Evaluation of the auxiliary diagnostic value of antibody assays for the detection of novel coronavirus (SARS-CoV-2)," *J. Med. Virol.*, vol. 92, no. 10, pp. 1975–1979, Oct. 2020.

[33] L. Zhao, F. Yang, L. Bu, S. Han, G. Zhang, and Y. Luo, "Driver behavior detection via adaptive spatial attention mechanism," *Adv. Eng. Informat.*, vol. 48, Apr. 2021, Art. no. 101280.

[34] A. S. Razavian, H. Azizpour, J. Sullivan, and S. Carlsson, "CNN features off-the-shelf: An astounding baseline for recognition," in *Proc. IEEE Conf. Comput. Vis. Pattern Recognit. Workshops*, Sep. 2014, pp. 806–813.

[35] F. Zhang, Z. Li, B. Zhang, H. Du, B. Wang, and X. Zhang, "Multi-modal deep learning model for auxiliary diagnosis of Alzheimer's disease," *Neurocomputing*, vol. 361, pp. 185–195, 2019.

[36] I. Azimi, T. Pahikkala, A. M. Rahmani, H. Niela-Vilén, A. Axelin, and P. Liljeberg, "Missing data resilient decision-making for healthcare IoT through personalization: A case study on maternal health," *Future Gener. Comput. Syst.*, vol. 96, pp. 297–308, Jul. 2019.

[37] F. Feng, Y. Wu, Y. Wu, G. Nie, and R. Ni, "The effect of artificial neural network model combined with six tumor markers in auxiliary diagnosis of lung cancer," *J. Med. Syst.*, vol. 36, no. 5, pp. 2973–2980, Oct. 2012.

[38] S. Gehlot, A. Gupta, and R. Gupta, "SDCT-AuxNet: DCT augmented stain deconvolutional CNN with auxiliary classifier for cancer diagnosis," *Med. Image Anal.*, vol. 61, Apr. 2020, Art. no. 101661.

[39] M. J. Maenner, K. A. Shaw, J. Baio, A. Washington, and P. M. Dietz, "Prevalence of autism spectrum disorder among children aged 8 years–autism and developmental disabilities monitoring network, 11 sites, United States," *MMWR Surveill. Summaries*, vol. 69, no. 4, pp. 1–12, 2020.

[40] D. American Psychiatric Association, and A. P. Association, *Diagnostic and statistical manual of mental disorders: DSM-5*, American Psychiatric Association, Washington, DC, 2013.

[41] M. Kaur, S. M. Srinivasan, and A. N. Bhat, "Comparing motor performance, praxis, coordination, and interpersonal synchrony between children with and without Autism Spectrum Disorder (ASD)," *Res. Developmental Disabilities*, vol. 72, pp. 79–95, 2018.

[42] E. A. Fuller and A. P. Kaiser, "The effects of early intervention on social communication outcomes for children with autism spectrum disorder: A meta-analysis," *J. Autism Develop. Disorders*, vol. 50, no. 5, pp. 1683–1700, 2020.

[43] A. Tryfon *et al.*, "Auditory-motor rhythm synchronization in children with autism spectrum disorder," *Res. Autism Spectr. Disorders*, vol. 35, pp. 51–61, Mar. 2017.

[44] K. K.-M. Stavropoulos and L. J. Carver, "Oscillatory rhythm of reward: Anticipation and processing of rewards in children with and without autism," *Mol. Autism*, vol. 9, no. 1, pp. 1–15, Dec. 2018.

[45] K. B. Martin *et al.*, "Objective measurement of head movement differences in children with and without autism spectrum disorder," *Mol. Autism*, vol. 9, no. 1, pp. 1–10, Dec. 2018.