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Design of a Hand Rehabilitation System Based on EEG Signals

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Abstract: In order to solve the problems of poor traditional rehabilitation training and the inability to achieve neuronal reorganization and recovery in stroke patients, a hand rehabilitation system controlled by EEG signals and classified by convolutional neural network was designed. The EEG signal acquisition module adopts the DSI-24 wireless polar brain acquisition system of Boruikang, the EEG signal processing method uses dual-channel CNN processing, the hand control system adopts the arduino development board and pneumatic rehabilitation gloves, and the signal processing and control software are completed in the computer. Design an experimental paradigm of motion imagination with two commands, left-handed and right-handed. Four participants were recruited to verify the feasibility of the system. Result The CNN recognition rate of five subjects reached 82%, the validation using the BCI2b dataset reached 85%, and the accuracy of the hand rehabilitation experiment reached 80%. Conclusions The results of this experiment verify the feasibility of rehabilitation gloves and provide a new method for the treatment of stroke patients.

Keywords: EEG, CNN, Hand Rehabilitation System

As people get older, they are more and more likely to suffer from a variety of diseases that endanger human health, such as stroke, as a serious cardiovascular and cerebrovascular disease. The disease is clinically characterized by its main features - disruption of blood supply to the brain and hemorrhagic damage - causing great distress and challenges to patients. Stroke is not only more common in the elderly, but also in recent years, it has also shown a trend of younger people.

Among them, Ueki of Gifu University in Japan and others [1] A hand exoskeleton rehabilitation robot based on virtual reality (VR) technology was developed, but due to the complexity of the design of the training equipment and the large size of the machine, it is only suitable for use in the ideal state of the laboratory, and the wearing process is cumbersome, which affects the enthusiasm of patients for rehabilitation. Researchers at Ulsan National University of Science and Technology, Korea, 2017[2] For the rehabilitation of damaged fingers in patients after stroke, a portable exoskeleton glove based on linear actuator motor and spring drive was designed However, the movement mode of the device is too simple, and the patient is fixed in a fixed position when using it, and there is no space for voluntary movement, which is easy to cause secondary injury in the event of an emergency. Wearable exoskeleton finger rehabilitation robot developed by Switzerland Federal Polytechnic University [3]. A wearable exoskeleton finger rehabilitation robot developed by the Federal Institute of Technology in Switzerland. Kati Pusiribi University in Izmir, Turkey, designed a Watt II six-link mechanism using the real grasping motion data of the index finger and applied it to a one-handed four-finger hand rehabilitation robot.[4] However, due to the different trajectories of the four fingers, it may cause harm to the patient. Finger rehabilitation robot developed by the National University of Singapore and Imperial College London [5] The robot is rope-driven, with each finger attached to a ring connected to the rope, and a clutch system designed to allow five fingers to be driven by only one motor. The differential force sensing system is designed to provide force feedback to the patient. However, the equipment is too large, and it is difficult for patients to operate it on their own and move freely. The finger rehabilitation robot in Austria is already a full-fledged commercial product [6] In order to reduce the number of drive motors, it simplifies the movement of the fingers and palms into a linear motion with a single degree of freedom. Before rehabilitation, stick the tips of your fingers to the finger cuff, and the magnet on the finger cuff can attach the finger cuff to the straight-line moving frame. When the robot drives the patient with too much force, the finger sleeve can be separated to protect the patient's safety. The rehabilitation manipulator Cybergroup of the United States Immersion company is separated from the driving mechanism, and each finger adopts the under-drive of a motor, which is compact in structure [7].

Researchers from Harbin Institute of Technology designed a passive finger rehabilitation training exoskeleton [8], this rehabilitation training exoskeleton mechanism is designed according to the physiological characteristics of the fingers to drive the fingers to complete the passive training, the four-finger part uses a miniature progressive motor for linkage control, the thumb part is driven separately by the linear push rod motor, the four-finger mechanism and the thumb mechanism are fixed on the back plate, and the back plate and the back of the patient's

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hand are matched with poor flexibility, for patients with severe finger injury In the process of rehabilitation training, when the finger muscles spasm, it is easy to cause secondary injury to the patient's fingers. Researchers from Huazhong University of Science and Technology designed a pneumatic device glove based on muscles, showing an exoskeleton rehabilitation training device, and the drive device is driven by both pneumatic muscles and torque springs, so that the fingers can complete control in two directions, which can be quantified. The control accuracy of pneumatic actuator is relatively low, the stability is poor, and it does not have high safety [9]. The finger rehabilitation robot developed by Yanshan University [10] uses a planar 3R mechanism to achieve four-finger flexion/extension movement, and by changing the number of teeth of the mediator wheel, the end of the connecting rod can move according to the natural movement trajectory of human fingers. It has a simple structure, but it cannot be used for single finger training. Finger rehabilitation robot designed by Beihang [11]. The robot is driven by Bowden wires and is equipped with angle and force sensors to facilitate measurements to obtain position and force information. The route is too complex, and it is difficult for patients to understand the operation, which affects the patient's recovery experience. Nanjing University of Aeronautics and Astronautics conducted research on the bending deformation prediction method of pneumatic mesh soft actuator [12] to establish a mathematical model of the bending angle of the actuator airbag and analyze its bending characteristics, so as to provide a theoretical basis for the design and control of the actuator.

The exoskeleton finger rehabilitation robot developed by Xi'an Jiaotong University [13] drives a multi-segment continuous structure through a single-layer spring blade to help patients perform flexion/extension movements. Because of the existence of the elastic element of spring sheet, this robot has certain flexibility, and the safety is better when using this robot to do rehabilitation training.

The research on the application of hand rehabilitation training robot has made some progress in recent years, there are still some deficiencies, 1 part of the exoskeleton mechanism design of rehabilitation training equipment is too complicated, and the wearing comfort is poor, because the fingers of postoperative rehabilitation training of stroke patients are mostly in a state of physiological damage, and the human hand is relatively fragile, when wearing a heavier mechanism, it is difficult to bear the weight of the mechanism, and it is easy to cause secondary injury to the fingers, which greatly affects the reliability and practicability of the rehabilitation equipment. 2. The rehabilitation mode of most finger rehabilitation training equipment is relatively single, mainly passive training, which cannot realize the patient's active training intention, and can only meet the early needs of rehabilitation training, and the movement space of the patient's fingers is small, and it is difficult to complete the requirements of rehabilitation training actions. In view of the above problems, the most important of which is that patients with severe stroke cannot complete rehabilitation training on their own, so this paper designed a hand rehabilitation system controlled by EEG signals and classified by convolutional neural network

1 OVERALL DESIGN SCHEME

1.1 SYSTEM COMPOSITION

The overall framework is shown in Figure 1 below, the system uses the DSI-24 wireless polar brain acquisition system of Boruikang to collect EEG signals, collects the patient's motor imagination through the EEG signal acquisition device, processes the brain telecommunications through the signal preprocessing module, filters and amplifies the brain telecommunications, and converts them into digital signals through digital-to-analog conversion In order to obtain the real motion intention of the patient in the collected EEG signal, the digital signal needs to be feature extracted, the characteristics of the signal are classified, different actions are judged, and finally the EEG signal of the class is input into the control system as a parameter, and the corresponding action is completed according to the patient's motor intention control mechanism.

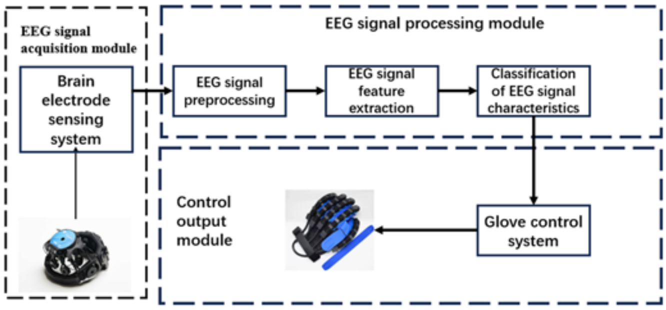

FIGURE 1 FLOW CHART OF THE REHABILITATION SYSTEM

1.2 EEG SIGNAL PROCESSING MODULE

Input layer: The original EEG signal passes through a 6th-order Butterworth bandpass filter of 0.5-40 Hz, and then the same filter is used to extract the EEG signals of the μ and β bands as the input of the model, and the input shape is as follows $R^{(B,1,T,N)}$, where B represents the batch size of the data, 1 is a new dimension added to adapt to the input of the model, T represents the length of the EEG signal, and N represents the number of electrodes of the EEG signal.

Temporal convolutional layer 1: This layer mainly extracts the characteristics of EEG signals in the time dimension, using the size of the convolutional kernel is 60 1×, the number of convolutional kernels is 8, the step size is set to 3*1, and the activation function adopts ReLU, and its expression is that $f(x)=\max(0,x)$ the Batch Normalization and Dropout strategies are used after the convolutional layer to speed up the training of the network and reduce the risk of overfitting.

Channel convolutional layer: This layer mainly extracts the correlation characteristics of EEG signals in the channel dimension, using the size of the convolutional kernel as the number of electrodes N, the number of convolutional kernels as 16, the step size is set to 1*1, and the other settings are the same

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as those of the temporal convolutional layer 1. Maximum pooling layer: Pooling is divided into average pooling and maximum pooling, and in this paper, the maximum pooling with a kernel size of 6*1 is used to reduce the size of the feature map and reduce the number of parameters of the model. Stitching layer: This layer is mainly to stitch the feature map extracted by the parallel spatiotemporal convolutional network in the time dimension, which is represented as $| \; R^{(B,C,T_1,1)} + R^{(B,C,T_2,1)} = R^{(B,C,T,1)}$, where $T = T_1 + T_2$.

Temporal convolutional layer 2: This layer mainly uses a small convolutional kernel of 3×1 to extract the depth characteristics of the EEG signal in the time dimension, the number of convolution kernels is 8, and the step size is set to 1×1, which can also play the role of feature fusion. Feature flattening layer: This layer mainly adjusts the dimension of the extracted EEG signal features, keeps the first dimension unchanged, and then reduces the next three dimensions to one dimension, that is. $R^{(B,C,T,1)} \rightarrow R^{(B,C*T)}$ Fully connected layer: The flattened features are taken as input, where the number of neurons in fully connected layer 1 is set to 100, The number of neurons in fully connected layer 2 is set to 2, which implements binary classification. Due to the large number of parameters in the fully connected layer, which is prone to overfitting, this paper adds a dropout strategy after the fully connected layer 1. Output layer: This layer is mainly to classify the features extracted by the model, here this paper uses the Softmax classifier, the purpose is to display the classification results in the form of probability, the classifier can be used for both binary classification tasks and multi-classification tasks. The data is shown in Table 1 below

TABLE 1 PARAMETERS OF PARALLEL SPATIOTEMPORAL CONVOLUTIONAL NEURAL NETWORKS

Layer type	Number of nuclei	Feature map size	Nucleus size	Step	Number of parameters
Output layer	-	1*1000*3	-	-	-
Time convolution 1	8	8*314*3	60*1	3*1	488
Channel convolution	16	16*314*1	1*3	1*1	400
Pooling layer	16	16*52*1	6*1	1*1	-
Splicing layers	-	16*104*1	-	-	392
Temporal convolution 2	8	8*102*1	3*1	1*1	-
Flatten the layer	-	816	-	-	816100
Fully Connected Layer 1	-	100	-	-	202
Full Link Layer 2	-	2	-	-	-
Softmax	-	2	-	-	

1.3 MODEL TRAINING OF PARALLEL SPATIOTEMPORAL CONVOLUTIONAL NEURAL NETWORKS

This model is based on pytorch 3.8.0 and is trained on a Dell server configured with Intel(R)core (TM) i7-10750H CPU@2.60GHz 2.59GHz and NVIDIA GeForce GTX 1660Ti. When training the model, due to the small number of EEG signal samples to prevent large overfitting of the model, the Dropout and Batch Normalization strategies are added in this paper. The former is known as random inactivation, and this method is able to set a given neural network activation value to 0, making it learn forward, making it have better learning performance. The latter is batch normalization of data, which mainly has the functions of accelerating the speed of model convergence, preventing overfitting, and preventing gradient explosion and gradient vanishing. The process of model training is shown in Figure 2 below.

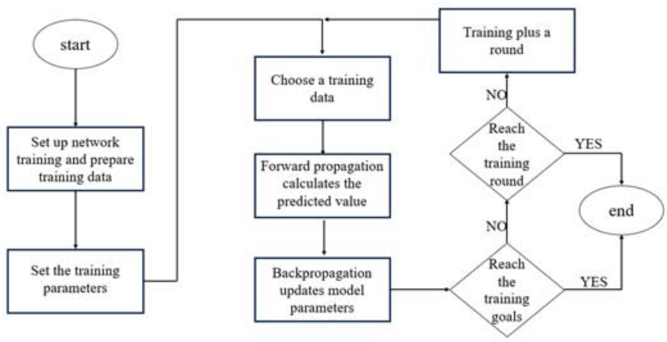

FIGURE 2 PSCNN TRAINING FLOWCHART

1.4 HAND EXERCISE GROUP MODULE

1.4.1 MASTER CONTROL MODULE

This design is developed using BIGFISH\BASRA as shown in Figure 3 below, and the device integrates 14 high-bandwidth digital input and output ports to ensure the efficiency and

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stability of signal transmission during data processing. It has 6 precision analog input channels to provide an accurate input interface for analog signals, and is equipped with a high-precision 16MHz crystal oscillator to ensure the accuracy of frequency output.

FIGURE 3 BASRA LAYOUT

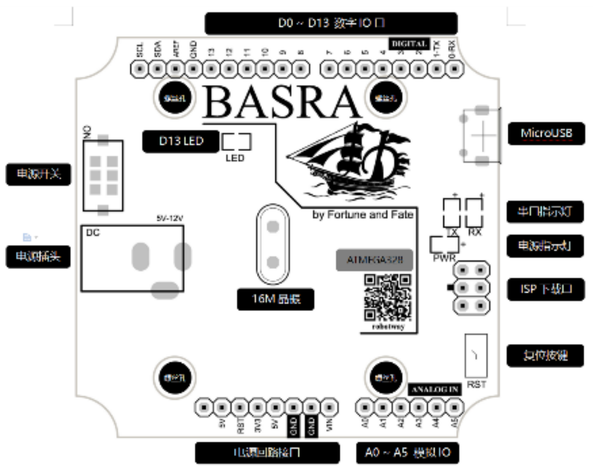

FIGURE 4 BASRA PIN SCHEMATIC

1.4.2 HARDWARE CONTROL MODULE

The 18650-lithium battery 12V/3000Hm battery is used for power supply, and the DC air pump control module L298N is used to control the DC12V micro air pump Small DC Vacuum Positive and Negative Pressure Pumping Pump-KMDP-C8 12V is used to provide the power part of the pneumatic glove. The following table describes the L298N schematic table, Table 2

TABLE 2 L298N PARAMETERS

Performance metrics	Specific parameters
Power supply range of the drive port	+5V~+35V
Excitation pulse current input and output	2A
Logical terminal power supply range	+5V~+7V
The amplitude of the operating current of the logic element	0~36mA
The input voltage regulates the amplitude of the signal	-0.3V Win 1.5V
Maximum power consumption	20W

The driver board is capable of driving two motors at the same time. When the state of the ports ENA and ENB is high, they come into play to ensure that the motor can function properly. Users can adjust the speed of the motor or change its running direction according to specific needs, so as to meet the needs of motor control in various application scenarios.

Table 3 shows the control mode and the status of the DC motor as shown below

TABLE 3 INSTRUCTIONS FOR USING L298N

ENA	IN1	IN2	DC motor status
0	X	X	Stop it
1	0	0	brake
1	0	1	Forward rotation
1	1	0	rollback
1	1	1	brake

The 2-way electromagnetic relay, as a key component in the circuit, works fairly simply and efficiently. The electrical signal is used to control the on/off of the circuit. When a control signal is applied to the relay, if there is no control signal input, then the relay is in an open state. The wiring diagram and physical diagram are shown in Figure 5 below.

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FIGURE 5 PHYSICAL DIAGRAM OF THE RELAY

1.4.3 SOFTWARE DESIGN MODULE

The software system uses Arduino software to write C language to control each component, first uses the Bluetooth protocol to receive the results classified by the convolutional neural network of the computer, and then defines the pins to control each component, realizes the generation and conversion of gas, and defines the delay function as 8 second's output. This cycle is shown in Figure 1-6 below

1.5 HARDWARE CIRCUITS AND THEIR GLOVES IN KIND

As shown in the numbers in Figure 9 below: 1 of them is the Bigfish and BASRA development boards, which are connected together in the form of upper and lower layers and are the main control part of the hand rehabilitation system, whose main task is to receive the left and right signals classified by the computer, and then output the signals from the pins. Its output controls 7, 8, 9.

2 and 3 are pumping/suction pumps KMDP-C8 12V, which can only operate in single phase, and there are strict requirements for positive and negative poles. The main task is to contract and unfold 10 (pneumatic rehabilitation gloves), in this diagram 2 is mainly responsible for air supply and 3 is mainly responsible for blowing.

4 and 5 are three-way solenoid valves, and their main function is to change the direction of the gas and finally realize the contraction and expansion of pneumatic rehabilitation gloves.

9 is the DC motor module L298N, which is controlled by Bigfish and BASRA pins, and his side output pins control the movement of 2 and 3.

7 and 8 are two-way solenoid relays controlled by Bigfish and BASRA pins, whose side pins control 3-way solenoid valves 4 and 5.

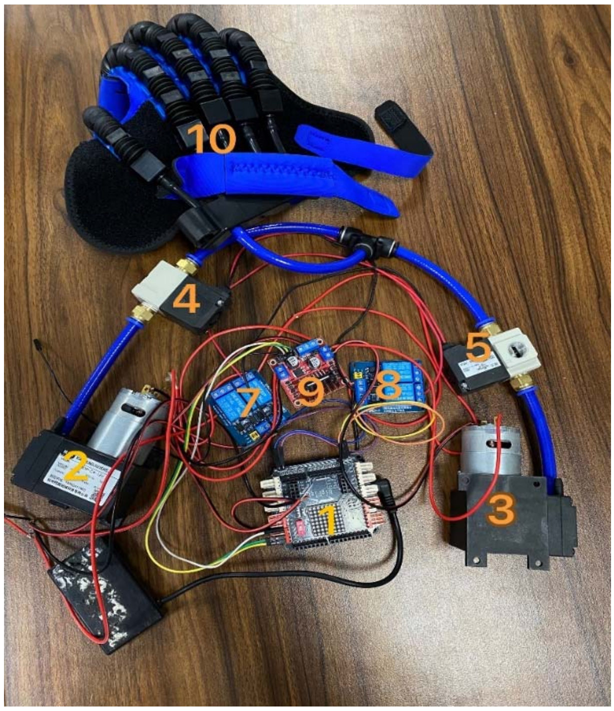

FIGURE 6 SCHEMATIC DIAGRAM OF THE PHYSICAL OBJECT

2 EXPERIMENTAL DESIGN

The effectiveness of the proposed PSCNN network in EEG signal decoding is verified, and the proposed method is compared with the traditional single-branch convolutional network (CNN2D). The Shallow ConvNet model in the traditional single-branch convolutional neural network reference paper [14] is constructed, which consists of an input layer, a temporal convolutional layer, a channel convolutional layer and a fully connected classification layer, and its model is similar to the proposed method, in which the convolutional kernel size and hyperparameter settings are the same as those of the PSCNN model. However, the method proposed in this paper uses a multi-branched structure to extract the characteristics of EEG signals in parallel. Experiments were conducted mainly on the BCI Competition IV 2b public dataset [15], and the following conclusions were drawn as shown in the figure below.

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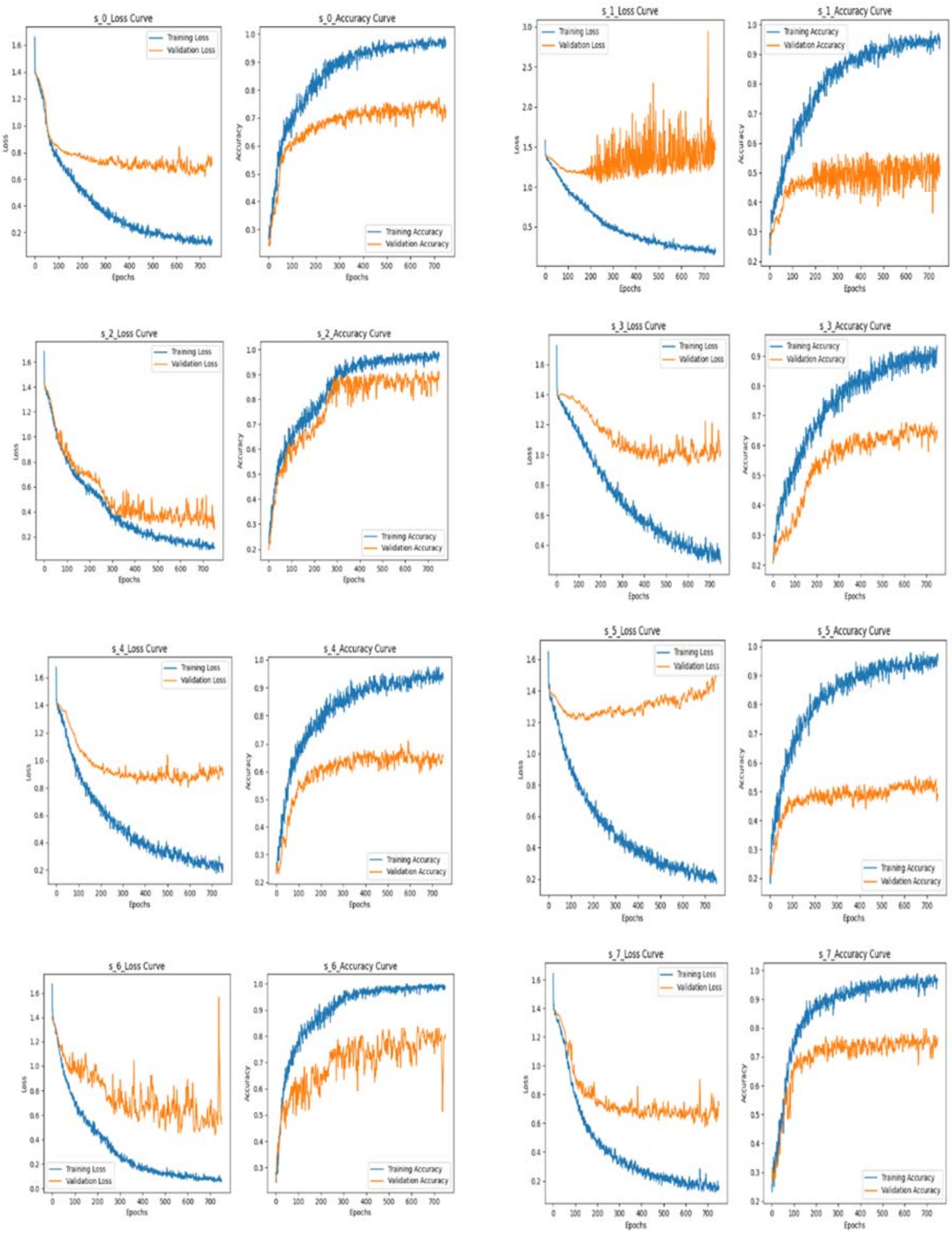

FIGURE 7 IMAGE OF PSCNN IN DATASET 2A

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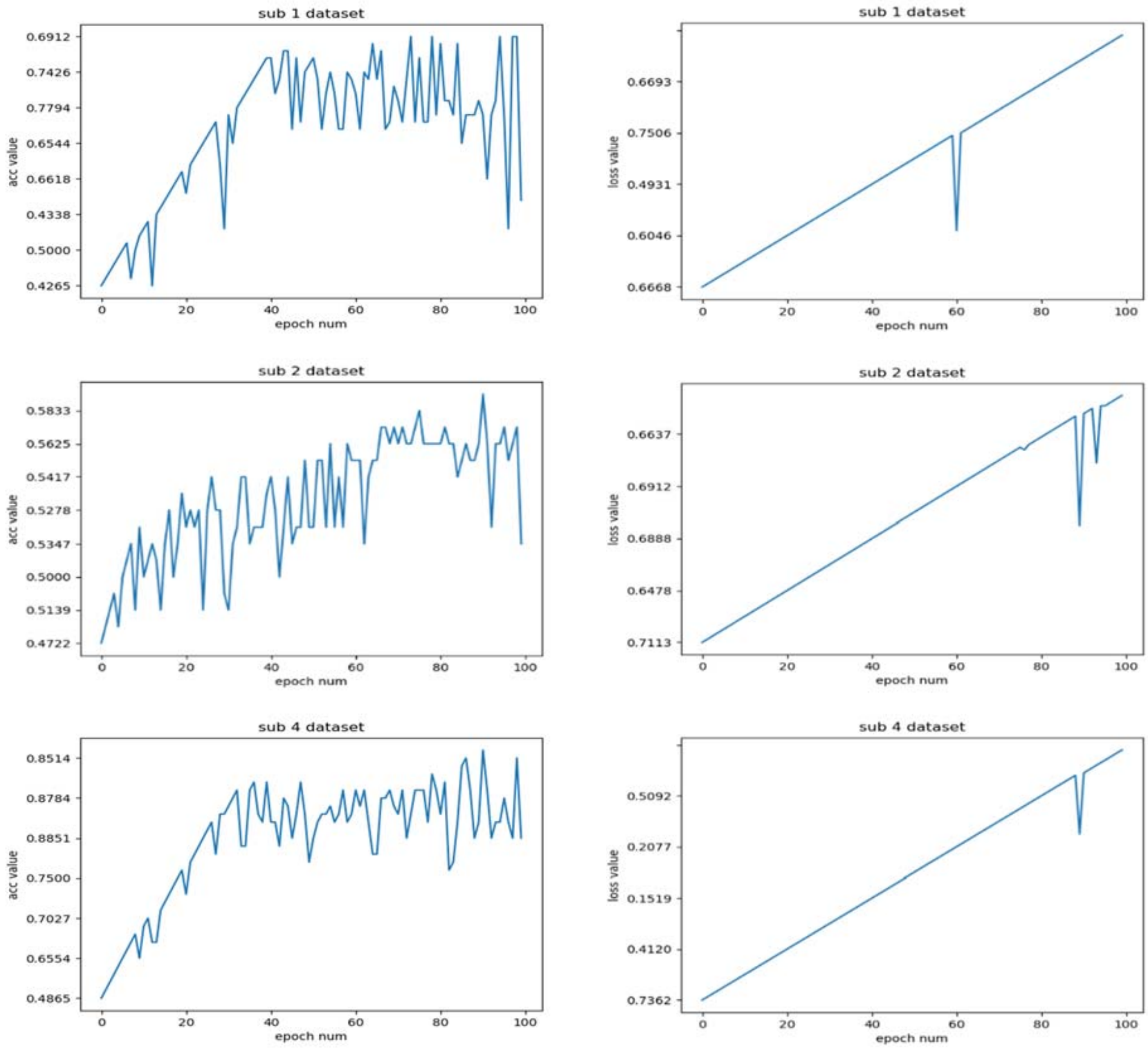

FIGURE 8 CNN2D IMAGE IN THE 2A DATASET

Classification results: The experimental results of the PSCNN method in dataset A are shown in Table 4, the average accuracy of the PSCNN method in dataset A is 83.46%, and the average accuracy of the CNN2D method is 75.5%, and overall, the PSCNN method proposed in this paper achieves a higher average accuracy than CNN2DUnfortunately, the standard error of the method proposed in this paper is larger than that of CNN2D. In addition, this paper also explores the classification performance of the proposed method using the original EEG signal (filtered 0.5-40 Hz and standardized preprocessing) as input, which is expressed as PSCNN*, and achieves an average accuracy of 84.17% and a standard error of 10.80%, which is better than the other two schemes in terms of average classification accuracy and standard error.

TABLE 4 CLASSIFICATION ACCURACY OF TRADITIONAL SINGLE-BRANCH CONVOLUTIONAL NEURAL NETWORK AND PSCNN ON DATASET A (%)

meth od	S1	S2	S3	S4	S5	S6	S7	S8
CNN 2D	69.5 %	59. 6%	-	85.5 %	-	-	-	-
PSC NN	85.4 2%	67. 4%	55.5 5%	97.2 9%	93.9 1%	89.5 8%	84.7 2%	88. 8%
PSC NN*	86.8 %	77. 2%	59.7 2%	97.2 9%	93.2 4%	85.4 1%	85.4 1%	83. 5%

To delve deeper into the complexity of EEG signals, we selected 4 testers, who were assigned the numbers A, B, C, and D. In each test, each participant will undergo four rounds of experiments, which include accurate acquisition of electrical signals and detailed classification of these signals. The sorted result data is successfully fed into a specially designed glove

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system. We carefully recorded all the results of the experiments so that they could be further analyzed and studied. In this way, we hope to be able to reveal the nuances of brain activity and provide new perspectives for understanding human cognitive processes.

Among them, we strictly control the conditions unrelated to the experiment, try to ensure the accuracy of the experiment and the authenticity of the effective data, according to the research shows that in the innovative work stage from 9 o'clock to 11 o'clock in the morning, because most people's heads are in a very active state during this time, the measured data is more accurate. Table 4 and Figure 8 are shown.

TABLE 5 CLASSIFICATION ACCURACY OF PSCNN ON SELF-COLLECTED DATASETS (%)

personnel	First experiment	Second experiment	Third experiment	Fourth experiment
A	80%	77%	79%	77%
B	78%	84%	83%	79%
C	79%	79%	83%	83%
D	82%	82%	80%	82%

As can be seen from the table, the classification of convolutional nerves in this paper is relatively accurate, basically around 82%.

3 CONCLUSION

The accuracy of CNN classification reached 82%, and the accuracy of online experiment of hand rehabilitation system reached 85%. Therefore, the system can greatly help patients achieve hand rehabilitation and has the advantages of comfortable wearing, strong applicability and easy to promote.

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