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Neuro-critical multimodal Edge-AI monitoring algorithm and IoT system design and development

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Abstract

In recent years, with the continuous development of neurocritical medicine, the success rate of treatment of patients with traumatic brain injury (TBI) has continued to increase, and the prognosis has also improved. TBI patients' condition is usually very complicated, and after treatment, patients often need a more extended time to recover. The degree of recovery is also related to prognosis. However, as a young discipline, neurocritical medicine still has many shortcomings. Especially in most hospitals, the condition of Neuro-intensive Care Unit (NICU) is uneven, the equipment has limited functionality, and there is no unified data specification. Most of the instruments are cumbersome and expensive, and patients often need to pay high medical expenses. Recent years have seen a rapid development of big data and artificial intelligence (AI) technology, which are advancing the medical IoT field. However, further development and a wider range of applications of these technologies are needed to achieve widespread adoption.

Based on the above premises, the main contributions of this thesis are the following. First, the design and development of a multi-modal brain monitoring system including 8-channel electroencephalography (EEG) signals, dual-channel NIRS signals, and intracranial pressure (ICP) signals acquisition. Furthermore, an integrated display platform for multi-modal physiological data to display and analysis signals in real-time was designed. This thesis also introduces the use of the Qt signal and slot event processing mechanism and multi-threaded to improve the real-time performance of data processing to a higher level. In addition, multi-modal electrophysiological data storage and processing was realized on cloud server. The system also includes a custom built Django cloud server which realizes real-time transmission between server and WeChat applet. Based on WebSocket protocol, the data transmission delay is less than 10ms. The analysis platform can be equipped with deep learning models to realize the monitoring of patients with epileptic seizures and assess the level of consciousness of Disorders of Consciousness (DOC) patients.

This thesis combines the standard open-source data set CHB-MIT, a clinical data set provided by Huashan Hospital, and additional data collected by the system described in this thesis. These data sets are merged to build a deep learning network model and develop related applications for automatic disease diagnosis for smart medical IoT systems. It mainly includes the use of the clinical data to analyze the characteristics of the EEG signal of DOC patients and building a CNN model to evaluate the patient's level of consciousness automatically. Also, epilepsy is a common disease in neuro-intensive care. In this regard, this thesis also analyzes the differences of various deep learning model between the CHB-MIT data set and clinical data set for epilepsy monitoring, in order to select the most appropriate model for the system being designed and developed.

Finally, this thesis also verifies the AI-assisted analysis model.. The results show that the accuracy of the CNN network model based on the evaluation of consciousness disorder on the clinical data set reaches 82%. The CNN+STFT network model based on epilepsy monitoring reaches 90% of the accuracy rate in clinical data. Also, the multi-modal brain monitoring system built is fully verified. The EEG signal collected by this system has a high signal-to-noise ratio, strong anti-interference ability, and is very stable. The built brain monitoring system performs well in real-time and stability.

Keywords: TBI, Neurocritical care, Multi-modal, Consciousness Assessment, seizures detection, deep learning, CNN, IoT.

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1. Introduction

1.1 Background

Traumatic brain injury includes a variation of brain function caused by external forces, such as scalp trauma, skull fracture, concussion, brain contusion, and nerve cell damage in brain tissue. Craniocerebral trauma is a public health problem that has attracted worldwide attention. The annual incidence of TBI in China is 55-64 per 100,000 population, causing nearly 100,000 deaths and further more disabilities each year [1]. Currently, traffic accidents have become the leading cause of TBI, which is also an essential factor leading to the disability of young people. Patients with TBI often suffer severe effects on their motor ability and cognitive function. Although patients with mild TBI can quickly recover after a short period of treatment, some others would probably get irreversible neurological damage. Furthermore, some patients would stay in a minimally conscious state (MCS) or a unresponsive wakefulness syndrome (UWS) for a long time [2, 3]. Meanwhile, the problem of aging in China is serious, and thus TBI caused by fall injuries has also increased significantly, making the death and disability rate of TBI higher in the elderly population. Improving the success rate of the treatment for TBI patients and improving their prognosis is the current focus of Neuro-critical medicine [4].

There are many types of TBI. In the past, most doctors use Glasgow Coma Scale (GCS) to classify the state of TBI [5, 6]. However, it is difficult to rely solely on the GCS score to quantify TBI patient's condition. And it is also challenging to make a more accurate assessment for the patient's condition. Benjamin proposed a multi-dimensional classification system that can evaluate TBI patients' condition more accurately [7]. With the continuous improvement on the medical conditions in China, such patients' mortality rate has gradually decreased, while the prognosis has gradually improved. According to related reports, the inpatient mortality rate of acute craniocerebral trauma patients in China is 4.6% [1], which has reached a developed states' level, in compare with 4.5% of EU countries. However, the prognosis of patients with craniocerebral trauma has always been a problem. To enhance the treatment, these patients are usually transfer to the Neuro-intensive Care Unit (NICU). Most of the NICU patients are in complex conditions, such as hypoxemia, hypotension, fever, hypoglycemia, and seizures. The fore mentioned symptom may also cause irreversible secondary neurological damage [8], which forces doctors to make quick and accurate judgments on the patient's condition in the treatment. With the development of modern medical technology, various medical electronic devices are applied increasingly in NICU. In addition to medical instruments that support patients' lives, various monitoring equipment also plays an important role. These devices collect the physiological information of patients and can provide doctors with much useful information, helping doctors diagnose the condition quickly and accurately.

Although many monitoring equipments have brought great convenience to NICU and have improved patient treatment success rate. However, since the conditions of NICU patients are very complicated, doctors often need to obtain more physiological information to make more accurate judgments. At present, most domestic and foreign neuro-intensive care equipment can only obtain a single physiological parameter. Multiple devices need to be connected to patients to acquire physiological parameters such as electroencephalogram (EEG), electrocardiogram (ECG), intracranial pressure (ICP), Brain regional O2 Saturation (rSO2). That has also caused unnecessary affairs for medical staffs in the implementation process.

On the other hand, some physiological signals such as EEG and ECG are quite complicated [9]. That make staffs must have related experience. Meanwhile, the presentation of information is not clear enough. Doctors need to rely on their own experience and manual analysis to make judgments. That makes different doctors' diagnosis a little different for the same patient. In recent years, artificial intelligence (AI) based on deep learning has been continuously developing [10]. Based on these physiological signals, the patient’s condition can be automatically judged, which significantly reduced the doctor’s work. At the same time, it will guide the doctors to make a more accurate diagnosis of the disease and give a more reasonable treatment plan. Neuro-intensive care is a cumbersome and time-consuming work. In clinical practice, medical staffs need to pay close attention to the changes in patients. However, the information exchange between doctors and patients is not smooth. To get patients' latest situation, medical staff often need to go to the bedside for observation. With the rapid development of AI and internet of things (IoT) [11]. It is imperative to build a whole smart medical monitoring system. That will improve doctors' efficiency in treating patients.

To sum up, neuro-intensive care is still facing various problems. Both the monitoring methods and the smart medical supporting systems need to be improved.

How to comprehensively monitor patients' physiological data, promote the intellectual development of medical diagnosis, and build an IoT ecosystem with all things connected are the current research directions.

1.1.1 Multimodal monitoring

At present, Neuro-intensive care is facing the problem of single monitoring indicators for most medical equipment. With the higher demand for Neuro-critical care, multi-modal monitoring methods have become one of the research directions of domestic and foreign experts [7, 12-15]. How to further improve the success rate of critically ill patients and improve their prognosis is still the focus of relevant scholars [16]. Necessary guardianship is one of the most effective methods. If the patient is not effectively monitored after the operation, the risk of potential diseases will also increase significantly [17-19]. In recent decades, various intensive care equipment has been used in Neuro-critical care, which has dramatically improved the prognosis of neuro-critical patients. The brain is the place where most neurologically critically ill patients occur. It is usually the main area for monitoring. As one of the most important tissues and organs of the human body [20], the brain has a more complex structure than other tissues and controls human physiological activities and other behaviors. Ability, any small factor may damage the brain, so it is necessary to minimize the patient's impact during monitoring. The condition of neurocritical patients is very complex, which requires more physiological data during the diagnosis process. Comprehensive physiological data has important guiding significance for diagnosis and can significantly improve its prognosis.

The multi-modal brain function monitoring proposed in recent years has become an internationally recognized method. It combines various neuro-function monitoring technologies based on traditional neuro-intensive care, which can monitor neurocritical patients with EEG, ICP, rSO2, CPP, Etc. Effectively integrate and analyze multiple parameters. The analysis of multi-modal signals can give more accurate diagnosis results than a single physiological signal, guide doctors to formulate the best treatment plan, improve the success rate of treatment, and improve the prognosis. In this case, a multi-modal brain monitoring system with a multi-parameter is urgently needed. Based on the existing multi-modal brain monitoring hardware system, this thesis research the relationship between various physiological indicators and diseases and realizes automated analysis of the collected physiological data.

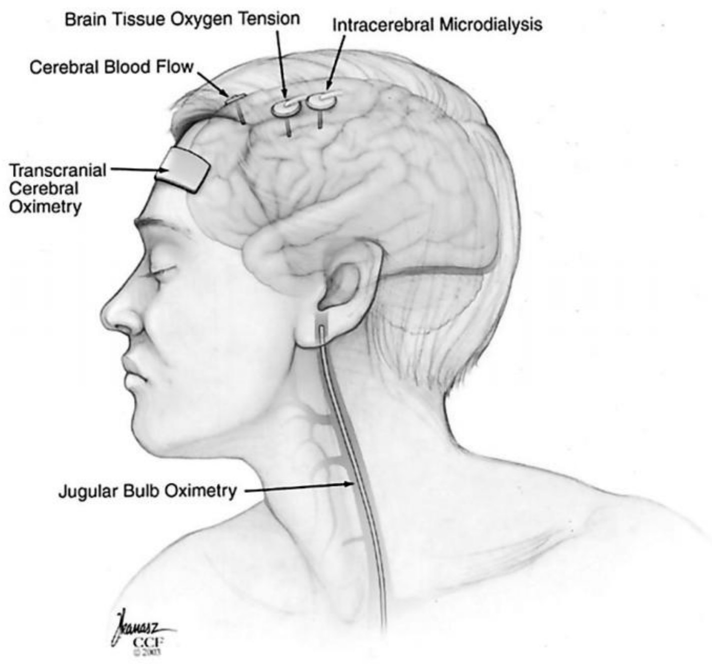


Figure 1.1 Multimodal monitoring system proposed by A. Michael [14]

1.1.2 IoT on NICU

In recent years, IoT technology has developed rapidly, and has been widely used in social life [21]. IoT products are gradually entering people's lives. Various wearable devices like home smart monitoring equipment, smart speakers, and smartwatches are spreading across all aspects of life, improving people's quality of life. The human being is also entering an era of the interconnection of all things and enjoying the convenience of IoT technology. The IoT technology application on the multi-modal brain monitoring system can bring great convenience to medical workers in NICU [22]. Most intensive care system was located at the bedside, and medical workers needed to go to the bedside to check physiological data. This working method seriously affected efficiency. Some patients' emergencies may not be reported back to the doctor in time, delaying treatment time. Thus, Building an IoT system based on the original multi-modal brain monitoring system will also solve this problem. Mobile Internet devices such as mobile phones have become standard tools in people's daily lives and are excellent carriers for information presentation. Establishing a connection between the physiological signal acquisition system and the mobile device can facilitate doctors to remotely view the patient's various physiological data and remotely diagnose diseases. That may change the current working model of medical staff and realize the intelligentization of medical procedures.

1.2 Research status

1.2.1 AI algorithm in disease diagnosis

Physiological signal acquisition is a very important task in the monitoring of nerve towns. Low-noise and accurate physiological signal is a good reference for doctors' diagnosis[23]. However, it is difficult for doctors to understand the original physiological data. Thus, signal processing and analysis are very necessary.

EEG is the most commonly collected signal in NICU, which contains various information about brain activity, and is the overall reflection of the electrophysiological activity of nerve cells on the cerebral cortex. Generally, different diseases make EEG signals have different forms. However, compared with other signals, EEG signals are difficult to process and analyze. Because it is like a non-stationary random signal, it is necessary to analyze the characteristics of EEG signals from multiple aspects due to the greater complexity of the signal itself. Among them, signal preprocessing, feature extraction, classification, or regression are important EEG signal processing and analysis contents. In the past signal preprocessing process, common space mode (CSP) [19], principal component analysis（PCA）[24, 25], common average reference [26], adaptive filtering [27], Independent principal component analysis, and digital filters are commonly used preprocessing methods. In terms of feature extraction: power spectrum density, PCA, wavelet transform [28], fast Fourier transform (FFT), Etc, are commonly used methods for feature extraction. However, power spectral density is generally not suitable for unsteady signals. PCA cannot handle complex data sets. Wavelet transform lacks an effective method for universal noise. Fast Fourier transform is also not suitable for unsteady signals, and cannot be analyzed in the time domain simultaneously and frequency domain characteristics. In the classification of EEG signals: K nearest neighbor algorithm (K-NN) [29], support vector machine (SVM) [30], naive Bayes [31], artificial neural network, Etc, are the commonly used classification algorithms in the past. However, these classification algorithms also have their limitations. The K-NN algorithm's generalization ability is too weak and requires larger storage space to store the samples. The support vector machine's calculation is complex, and the generalization ability is mainly aimed at a relatively small sample size. It is also relatively weak. Naive Bayes needs to keep feature variables independent of each other. ANN's performance is very dependent on the number of hidden layer neurons [32].

However, classifying the extracted features and correlating the classification results with widespread diseases is a vital EEG analysis. Therefore, it is necessary to explore a universal algorithm to process EEG signals. As a new machine learning field, deep learning has gradually highlighted its advantages in EEG signal analysis. Among them, Deep convolutional neural networks (DCNN) [33] are more widely used. Traditional machine learning methods require much time for feature extraction, and generally need to specify the extracted features manually, and then classify. This method is less efficient and easy to lose some useful information, while deep learning takes the original EEG signal as input, no additional feature extraction and selection are required, and the original EEG information can be retained to the greatest extent. Neuro-intensive care often produces a large amount of data during the monitoring process. These data will be discarded after being used and not fully utilized. However, deep learning combined with big Data can better play its role [34]. The trained neural network is often more reliable with big Data.

At present, many researchers have applied deep learning to medical diagnosis. Sheth pointed out that artificial intelligence can help patients make better decisions regarding personal health [35]. Xiaoxuan Liu et al. found that the AI deep learning algorithm can correctly detect diseases in 87% of cases, compared with 86% for professionals [36]. In medical image processing, Liu used Deep Learning and magnetic resonance imaging technology to diagnose Alzheimer's disease (AD), the accuracy can reach 91.4% [37]; Spampinato used a deep learning model to assess the bone age automatically [38]. Jiao used CNN to extract different in-depth features to improve the accuracy of breast cancer classification [39]. Many scholars have also proposed corresponding deep learning models for disease diagnosis in terms of electrophysiological signal processing. For example, Wu proposed a deep learning model used in the diagnosis of arrhythmia. This model can diagnose 12 types of arrhythmia with an accuracy of 83.7%, exceeding 78% of human cardiologists [40].

In addition to medical imaging and ECG signal applications, deep learning is also applied to complex EEG signals. Disease diagnosis is one of the essential directions of deep learning in EEG signal research. Many scholars build suitable network models based on EEG signals and have achieved good results in disease diagnosis. Ren pointed out that deep learning models based on convolutional neural networks can better extract features from multi-channel EEG signals [40]. Supratak proposed a network framework for automatic detection of sleep state-Deep SleepNet [41]. This method achieved 86.2%-81.7 accuracy based on single-channel EEG signal detection. Samiee proposed using Short-Time Fourier Transform (STFT) to extract the features and then using a multilayer perceptron to classify epilepsy [42], and the accuracy rate reached 99% in the best case. Morabito used the CNN network model to extract single-channel EEG signal characteristics for Alzheimer's disease detection, and its accuracy rate reached 80% [43].

From previous studies, it can be found that the performance of deep learning network models depends not only on the structure of the network but also on the method of feature extraction. Therefore, many scholars put forward many suggestions for improvement based on these two aspects. For example, some scholars have begun to try to change the feature extraction method to improve disease diagnosis accuracy. Since the EEG signal's characteristic performance in the time domain is not apparent, the researchers used short-time Fourier transform (STFT) to convert the EEG signal from time-domain to time-frequency domain [44]， and analyze the signal and extract the characteristics of the signal from the two dimensions of the time domain and the frequency domain. CNN is also better at two-dimensional (2D) processing signals, Thus， Using 2-D CNN models usually make the diagnosis of certain diseases more accurate. Also, discrete wavelet transform is a common method to extract signal features. For example, A. Sharmila and others combined a discrete wavelet transform and artificial intelligence classification algorithm to achieve epilepsy detection [45], and its detection accuracy reached Around 97%. In addition to improving network performance by changing feature extraction methods, many scholars have also improved network structure to improve performance. For example, Yuan proposed a multi-angle deep learning framework for epilepsy detection in 2019 [46]. The learning framework combines supervised learning and unsupervised learning methods and uses STFT methods. That makes it possible to achieve an average accuracy of 94.37% in epilepsy detection. Chambon proposed a multi-variable and multi-modal time-series deep learning framework [47], which integrates EEG, electromyography (EMG), electroOculography (EOG) signals related to sleep states, and Combine them and take all the features into the classifier, and the accuracy of the model in some sleep states can reach 89%.

Epilepsy is a common disease worldwide. One out of every 100 people has Epilepsy. Epilepsy brings great pain to patients. In order to detect epileptic seizures in time, many scholars have proposed many methods. In 2009, Tzallas used STFT to convert EEG signals from time-domain analysis to time-frequency analysis. By building an ANN model to achieve epilepsy detection, the model's accuracy reached 89% [48]. Recently, the accuracy of the proposed network model by Yuan can reach 94.37%.

Nearly 100,000 critically ill patients in China fall into a coma and enter a state of long-term disorder of consciousness each year. The two types of UWS and MCS are the most common in the judgment of consciousness disorders. Among them, patients with a minimally conscious state have a higher residual consciousness level and a higher possibility of recovery. However, the current judgment method mainly relies on the doctor's observation and scale score, and the misdiagnosis rate reaches 40% [49]. Many studies have shown that EEG signals are related to disorders of consciousness. In 2018, Denis proposed a robust EEG-based cross-site and cross-protocol classification method with the best accuracy with 0.78 [50].

Although many scholars have achieved excellent disease diagnosis results based on deep learning artificial intelligence algorithms, many studies are based on open-source data sets with good data quality, and their methods have not been clinically verified. That is also a reason why some artificial intelligence algorithms have not been practically applied. More complicated clinical situations, like collected data may contain more noise, which requires data processing and AI algorithms to adapt to these situations. That has higher requirements for the robustness of the network model. Also, the data sets used by many current AI algorithms do not contain various subjects. However, the combination of AI algorithms and the massive data provided by the IoT can better meet deep learning requirements for big data.

This thesis does an in-depth analysis of seizures detection and disorders of consciousness with the EEG signal. Furthermore, it builds deep learning models based on actual needs and applies it to the IoT system.

1.2.2 Research status of IoT technology in NICU

IoT technology is one of the most popular technologies at present. With the continuous improvement of computer computing power and the promotion of 5G technology, IoT has also developed rapidly, gradually affecting the social production methods and human lifestyles. At the same time, The Internet of Things technology is also the core of future smart medical care. In order to establish a real-time and efficient medical control and management system, the comprehensive application of multiple technologies has become one of the development directions of IoT, including sensor technology, RFID technology (radio frequency identification), wireless communication technology, data processing technology, and network technology, voice recognition technology, Etc [51]. The development of these technologies also promotes the development of medical IoT technology. In recent years, many scholars have proposed many specific IoT applications in medical monitoring. For example, Catarinucci proposed a smart hospital system (SHS) using radio frequency identification (RFID) and wireless sensor network (WSN) Used to monitor patients [52]. Verma proposed a patient health monitoring system based on Fog Computing [53], with the artificial intelligence algorithm classifiers. The proposed Bayesian belief network classifier-based model has higher accuracy when compared to other classifiers.

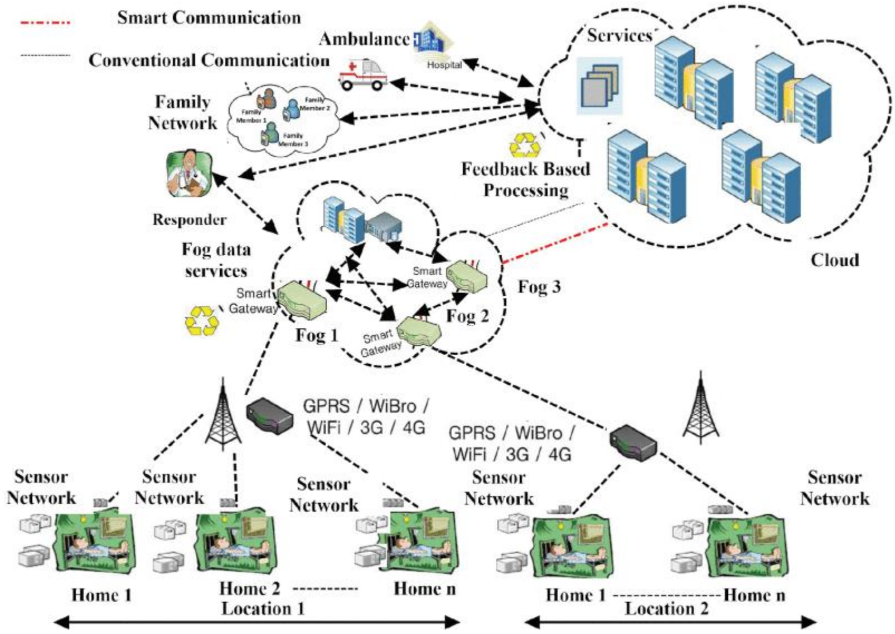


Figure 1.2 IoT system proposed by Verma [53]

IoT has also developed rapidly in China, and various IoT products have been applied to daily life, such as smart furniture and smart medical monitoring equipment. These applications are mainly for ordinary consumers. However, few relatively IoT applications are used in hospitals, and most IoT applications in hospitals are concentrated in personnel management, medical procedures, health management, Etc. Yang proposed an IoT system for remote pain monitoring, and the system can automatically assess pain based on facial expressions. This thesis integrated AI algorithms into the IoT system to automatically classify seizures and access disorder of conscious of helping patients diagnose diseases.

1.3 Major works and contributions

This thesis develops software systems and researches on AI algorithms based on EEG signals with the hardware system designed by our lab team. and cooperates with the Huashan Hospital affiliated to Fudan University. They provided large amounts of clinical data， And this thesis uses the provided data to build a properly deep learning model and verify the model with data collected by the developed hardware system.

The main work of this thesis is as follows:

1. Data visualization software system was designed at the bedside. NVIDIA Jetson@TX2 is used as the host computer, and the software system for data visualization is started on this platform to observe and analyze the collected electrophysiological signal data.

2. Back-end server on the cloud server was developed to optimize data management. The MongoDB database is deployed on the cloud server. During the data collection process, the host computer will push the data to the cloud server database for real-time storage. Also, real-time communication will be established between the cloud server and the WeChat applet.

3. Research on deep learning algorithms based on assessment in disorders of consciousness: This thesis is based on various physiological data collected by Huashan Hospital in clinical diagnosis. Combining deep learning algorithms, build a suitably deep learning network, assess the patient's level of consciousness disorder.

4. Analysis of deep learning algorithms based on epilepsy monitoring: In the past epilepsy monitoring algorithms, most researchers have proposed useful monitoring algorithms based on public data sets. These algorithms have quite good results in some public data sets. However, in practical applications, the collected data is often quite different from the data in these standard data sets, and various environmental factors will also have a more significant impact on the results of the judgment. For this reason, this thesis discusses the difference between the different existing network model in the public data set and clinical data, and choose a proper clinical application plan.

The main innovations of this thesis are as follows:

1. Combining clinical data, try to use deep learning methods to evaluate patients' consciousness level with consciousness disorders. Also, a deep learning model suitable for this article is selected based on existing models to monitor patients for epilepsy.
2. Combine the deep learning model to build a intelligent multimodal brain monitoring IoT system in NICU.

1.4 Chapter Summary

This chapter mainly introduces the thesis's research background and the current research status, including the problems faced in neuro-intensive care. The physiological indicators collected by the monitoring equipment are single, and comprehensive physiological data cannot be provided. Artificial evaluation of the consciousness level of patients has a very high error rate. Although deep learning based on epilepsy detection is highly accurate, it has not been fully verified clinically. During neuro-intensive care, doctors do not receive patients’ information in time, which delays treatment time. This chapter also introduces some significant research results of deep learning in disease diagnosis, and in some aspects, AI algorithms based on deep learning are better than professionals in the diagnosis of certain diseases. IoT is one of the development directions of future science and technology. IoT technology, which integrates artificial intelligence and other high-tech technologies, will improve medical diagnosis's intellectual level. Finally, the main contributions and innovations of this article are introduced.

2 System architecture and algorithm requirement analysis

This thesis adopts a multi-modal brain monitoring system developed by the laboratory. The system mainly includes signal acquisition control system, EEG signal acquisition module, Near-infrared spectroscopy (NIRS) acquisition module, ICP acquisition module, upper computer platform equipment, display device, etc. The software algorithm mainly contains signals Preprocessing, feature extraction, and deep learning algorithm analysis based on consciousness disorder assessment and epilepsy detection.

2.1 System structure design

2.1.1 System composition

The multi-modal monitoring hardware system includes the collection of a variety of physiological signals. Not only that, the hardware system reserves an expandable signal interface, which reserves space for the collection of more physiological signals in the future. In terms of neuro-intensive care, EEG signals, NIRS signals, and ICP signals are the most frequently observed signals. These signals contain a large number of signals that can assist doctors in medical diagnosis. Therefore, the hardware system mainly takes the central acquisition module as the core, with external EEG signal, NIRS signal, and ICP signal acquisition modules. These modules together constitute a physiological signal acquisition platform. Not only that, through FPGA, the acquired signals are processed in real-time, and power frequency and other noises are filtered out to ensure signal integrity and reliability.

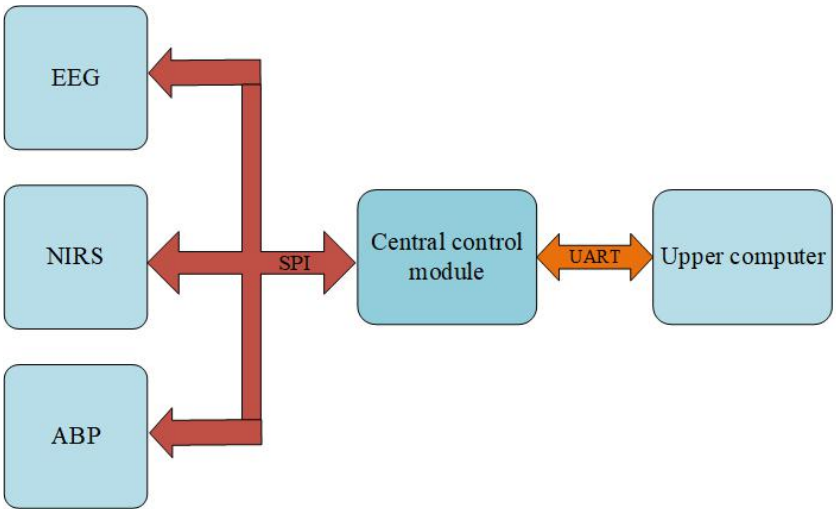


Figure 2.1 Hardware system structure

2.1.2 System function module overview

1) EEG signal acquisition Model

The EEG signal amplitude is very small, usually only 10 to 100μV. Therefore, the selection of EEG electrodes during the acquisition process is also crucial [54]. It is necessary to choose materials with the smallest resistance. This system uses gold-plated electrodes that the impedance is small. To further reduce the impedance between the skin and the electrode, skin cleansing gel is used to remove the oil on the skin during the measurement, and conductive gel is applied between the skin and the electrode to make the skin and the electrode better fit. Due to its very weak EEG signal, it is very easy to receive external factors interference during the acquisition process. The neuro-intensive care room usually has many equipment, some ventilators that maintain the patients' lives, solution infusion pumps, vibration sputum expectoration, and other electronic instruments easily yield electromagnetic interference and vibration interference. This thesis's hardware system fully considers these factors and ensures the EEG signal is more accurate and reliable by using an independent power supply, improving filter design, and adding electromagnetic shielding equipment.

In actual application, if the patient installs too many EEG electrodes, it will increase the doctor's workload and make the operation more difficult and reduce the patient's comfort. The fall of the electrode and the patient's position also makes it impossible to collect complete information during the signal acquisition process. If there are too few electrodes, the patient's brain's complete EEG activity information cannot be collected. Generally, eight channels of EEG signal are satisfied for doctors. For this reason, the system uses 8 EEG electrodes. According to the brain's distribution of 10-20 brain regions, it can be installed at F3, F4, P3, P4, C3, C4, T3, T4. Nevertheless, the position is not fixed. The doctor can adjust it according to the actual condition of the patient.

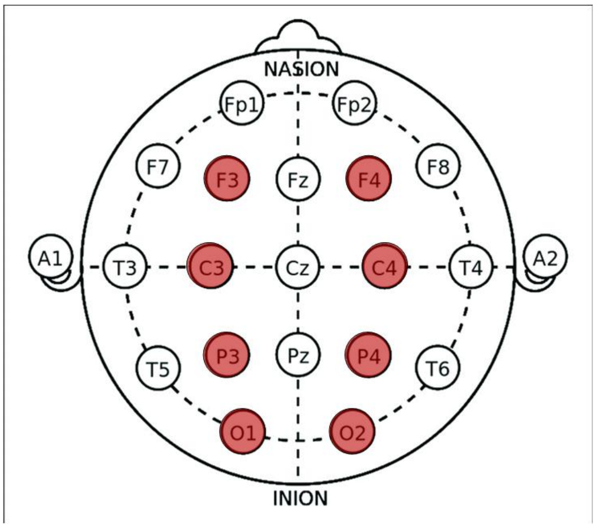


Figure 2.2 International 10-20 EEG System [55]

2) NIRS signal acquisition Mode

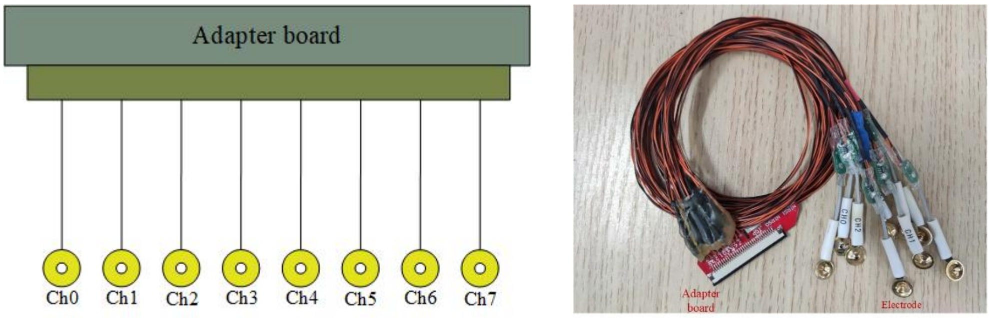


Figure 2.3 EEG Electrode Structure

The NIRS measurement method has been widely used in measuring blood oxygen saturation. According to statistics, China is the largest country with a stroke， an acute cerebrovascular disease causes brain tissue damage, mainly due to the sudden rupture of blood vessels in the brain or blood cannot flow into the brain due to vascular blockage. Its fatality rate and disability rate are in Ranked first in the world. Neurologically critically ill patients are also prone to cerebral ischemia after surgery. By monitoring the cerebral blood oxygen saturation, the patient’s condition can be observed in time. Based on the NIRS cerebral blood oxygen monitoring method, it can realize real-time, continuous, and non-invasive monitoring of the brain's oxygen saturation. According to the Beer-Lambert law, near-infrared light with a wavelength of 650nm to 850nm can penetrate human skin and bones. Oxyhemoglobin and deoxyhemoglobin in blood tissues have different absorption rates for different wavelengths of light. The blood's oxygen saturation is calculated by monitoring the reflected intensity of light beams of different wavelengths after passing through the human body [56].

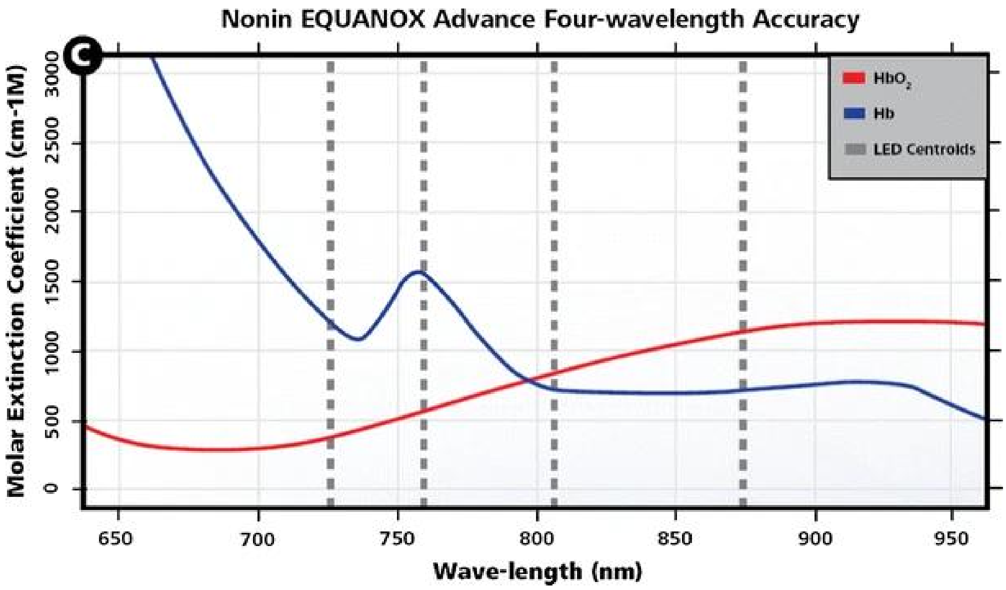


Figure 2.4 Specific extinction coefficients of HbO2 and Hb [57]

Blood oxygen saturation is also a physiological indicator that is often considered in intensive care. This system's NIRS signal acquisition module is mainly placed on the patient's forehead to get the patient's brain blood oxygen saturation. In order to monitor both sides of the brain at the same time, the system is equipped with two NIRS signal acquisition modules, which can monitor the blood oxygen status of the left and right brain in real-time. The acquisition module mainly includes the light-emitting part and the receiving part. The collected signal is processed in real-time on the host computer to reach the final result.

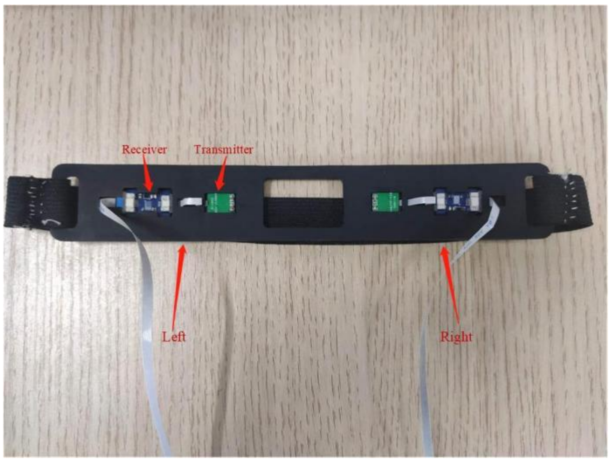


Figure 2.5 NIRS signal collection model

3) ICP signal acquisition model

Intracranial hypertension is a common syndrome caused by increased brain parenchyma and its fluid volume caused by various diseases [58]. In severe cases, it can rapidly develop into cerebral herniation and endanger life. It is also an essential physiological parameter in neuro-intensive care. Many scholars have found that ICP monitoring can reduce patients' mortality with severe traumatic brain injury and improve their prognosis. Many doctors and scholars recommend routine ICP monitoring. However, ICP is a physiological signal that is difficult to monitor. So far, the invasive ICP method is still the gold standard for ICP measurement. Although some domestic and foreign scholars have proposed various non-invasive ICP monitoring methods [59], most monitoring methods' accuracy cannot meet the demand. In this hardware system, the ICP measurement module is placed in the skull and uses a wireless power supply and NFC to transmit data. The specific principle is not described in detail in this thesis. The module is shown in the figure below.

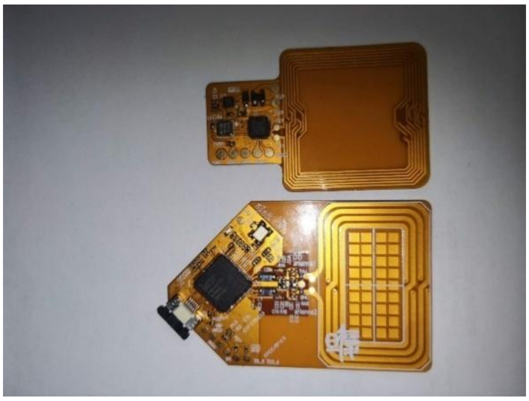


Figure 2.6 The ICP model

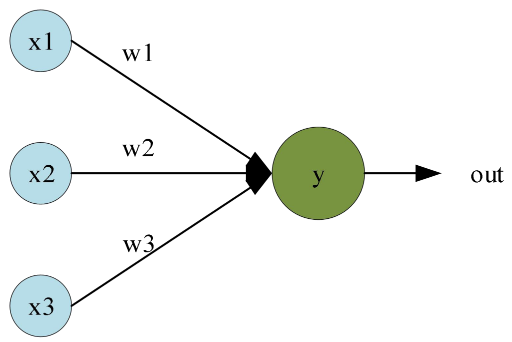
2.2 Analysis of algorithm requirements in the system

In the Algorithm, this thesis mainly uses artificial intelligence algorithms to assess patients' consciousness levels with impaired consciousness and determine whether they have a seizure. Combined with clinical data, analyze how signal processing and artificial intelligence algorithms are implemented in EEG signals.

2.2.1 Deep learning introduction

In this thesis, the evaluation of consciousness disorder and the diagnosis of epilepsy is based on convolutional neural networks. Therefore, in this chapter, we will introduce related deep learning algorithms, especially convolutional neural networks.

Deep learning is an essential branch of machine learning. Unlike other algorithms, deep learning is based on big data. Among them, deep convolutional neural networks are the most widely used. Deep learning network models mimic the structure of the brain. There are about 80 million neurons in the human brain. These neurons are responsible for the nervous system's functions and control the human body's physiological activities and daily behaviours. A neuron usually has multiple dendrites, mainly used to receive information. While there is only one axon, and many axons end at the end of the axon that can be used to transmit information, and the axon ends are connected to other neurons' dendrites simultaneously. Thus, thousands of neurons together form a complex neural network, which can realize very complex functions. The deep convolutional neural network is similar, and its mathematical model as Figure 2.7.



$$y = x * w \tag{2-1}$$

Figure 2.7 Neuro cell and mathematical model

A simple neuron model involves necessary input, output and corresponding weight parameters. The training process of a neural network is the process of continuously optimizing the parameters in the network. Since the 1980s, convolutional neural networks have been used in the field of computer vision. However, in recent years, with the improvement of computer computing power, it is possible to build a more complex network structure and combine big data for network training, so that deep convolutional neural networks have made more significant breakthroughs in the field of image recognition. Simultaneously, deep convolutional neural networks are also applied in more aspects, such as natural language processing (NLP), signal analysis, Etc.

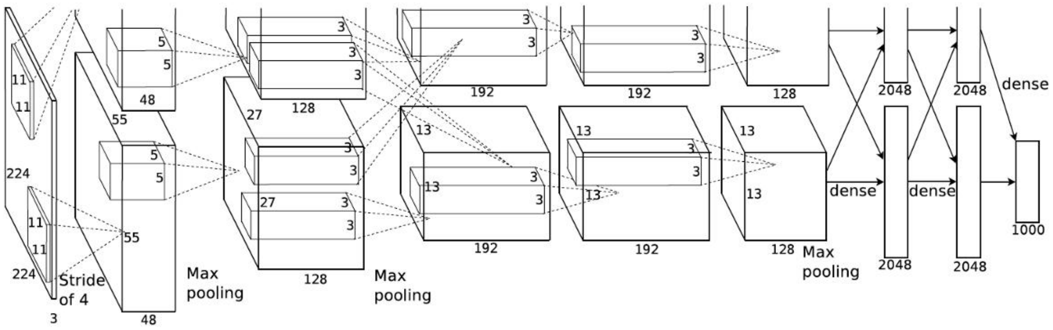


Figure 2.8 AlexNet structure [60]

CNN has an apparent hierarchical structure as Figure 2.8. A complete CNN usually contains the following layers:

(1) Convolutional layer: It is mainly used for feature extraction. It convolves with the input signal by setting a corresponding size convolution kernel, and the result is used as the input of the next layer of the network.

(2) Pooling layer: Down-sampling the input data and sparse processing of features can reduce redundant information to a certain extent, reduce over-fitting, and accelerate the training process. Common pooling operations include maximum pooling, minimum pooling, and average pooling.

(3) Fully connected layer: usually connected to the convolutional layer. Its principle is similar to that of a multi-layer perceptron. Its purpose is to use the features extracted by the convolutional layer to perform classification processing to obtain the final result. In many cases, the fully connected layer often needs to set more layers.

CNN model can be traced back to the 1960s. Hubel recorded neurons' activity in the cat's brain and systematically created a map of the visual cortex through experiments [61]. Kunihiko Fukushima proposed a neural network with a convolutional layer and a pooling layer in 1988 [62]. Many current deep learning algorithms have also been established on this basis. In 1998, Lecun proposed a LeNet-5 neural network [63], which applied the BP algorithm to the neural network for training, forming the current CNN network prototype. In 2012, AlexNet proposed by Hinton [60], and in the Imagenet image recognition competition, it reduced the recognition error rate to 15%. Since then, Simonyan and Zisserman proposed a deeper VGG model in 2012 [64], Google extracted the Inception network structure in 2014 [65], Kaiming He proposed the ResNet model in 2015 [66], and Zhang Xiangyu extracted the ShuuffuleNet (SEnet) model in 2018 [67]. Based on the ImageNet data set, the recognition error rate of these models has gradually decreased, and the recognition error rate of SEnet has reached 2.25%, which is lower than the human error rate of 5%.

The CNN network model uses convolution operations to extract the input data features, which also follows the traditional classification algorithm, but there are essential differences in feature extraction. In traditional feature analysis, we need to define the input signal feature artificially, such as mean, variance, entropy, Etc. These features often have strict definitions and cannot be changed at will. These characteristics are often important ways of analyzing data in the past. However, in deep learning, we do not strictly define the characteristics of the data, but through big data training, let the neural network automatically find the input signal's characteristics. That expands the types and scope of feature extraction to a certain extent, and as the network is trained, the network can automatically assign appropriate weights to each feature. That is one of the reasons why deep learning is so popular today.

Compared with CNN, the RNN network is mainly used in natural speech processing or some one-dimensional signals. This kind of network is very suitable for processing signals that are correlated in sequence. For example: in natural language processing, speech is a one-dimensional signal. To obtain the complete information of a sentence, we need to consider the overall meaning of a sentence, and even the content of the previous sentence, not a single word. However, when dealing with non-stationary random signals like EEG, it is often of no great use.

Nevertheless, deep learning still faces particular bottlenecks and challenges. For example, deep learning requires a large amount of labelled data to improve the model's generalization ability. Deep learning often requires many data sets, which makes researchers collect data sets based on this. Secondly, deep learning will overfit the benchmark data. Finally, deep learning is sensitive to changes in input signals, such as images. When the input data receives external interference, it will seriously affect the judgment of the network.

2.2.2 Deep learning with EEG signal

In medical and health care, deep learning has also been widely used, especially in physiological signals. From common CT images to one-dimensional electrophysiological signals, deep learning gradually exerts its advantages in processing these signals. It is one of the current hot research directions. Compared with other electrophysiological signals, the EEG signal is quite different. From the signal itself's perspective, the signal reflects the change of brain activity and has enormous complexity. There are also difficulties and challenges in signal analysis.

Difficulties of EEG signal analysis:

1. The signal is weak. Compared with common electrophysiological signals, such as ECG, ECG. EEG signals are weaker, making it easy Interfered by external environmental factors in the signal acquisition process. The data will introduce some noise to a certain extent, making us need to seek better solutions in signal denoising.

2. The signal has greater complexity: Compared with other signals, EEG signals will show non-stationary random signals' characteristics.

In the common EEG signal analysis method, many scholars usually combine time-domain analysis and frequency domain analysis results for comprehensive evaluation. That is also the primary method of physiological signal analysis at present. For this reason, choosing a suitable feature extraction method is After learning the main points of research by many scholars, the selection of features and the extraction methods will directly affect the results of signal analysis.

2.3 Chapter summary

This chapter mainly summarizes the multi-modal brain monitoring hardware system and the function of each module. These modules together constitute the hardware platform of the system. As an essential part of the system, it provides reliable data for subsequent research on artificial intelligence algorithms. Secondly, this chapter introduces the theoretical knowledge of deep learning and its application in medical and health care. Although deep learning has been widely used and popularized, the research and development of deep learning have also encountered bottlenecks, which are also challenges facing the future.

3 Consciousness assessing based on deep learning

Assessing the residual consciousness of patients with disorder of consciousness (DOC) is an important clinical issue, and a reliable assessment result is of great significance for improving their prognosis. However, there is a large error rate in manually evaluating the patient's level of consciousness. Based on the EEG signal, this chapter uses a deep convolutional neural network to assess the patient's level of consciousness automatically.

3.1 Dataset

At present, there is no useful open source data set for evaluating the level of consciousness disorder. Therefore, this thesis uses clinical data provided by the Department of Neuro Intensive Care of Huashan Hospital of Fudan University to analyze patients' different manifestations with consciousness disorders in MCS and UWS. It contains the EEG data of 12 patients with impaired consciousness, and each patient has suffered different degrees of brain damage. This article does not describe patients' relevant personal information to ensure the privacy of patients, but only briefly explains the data.

These patients have suffered severe head injuries, such as cerebral hemorrhage, respiratory and cardiac arrest, severe head trauma, central nervous system infection, and infarction after brain stem hemorrhage. Among them, 6 patients were in a UWS with a poor prognosis, even died. And 6 patients were in a state of MCS with a good prognosis that can take care of themselves. Some patients can take care of themselves after a period of rehabilitation. As can be seen from Table 3- 1, patients' prognostic status cannot be assessed by the GCS scale, which is one of the problems to be solved in this thesis.

Table 3- 1 Information of Patients

Subject/	Gender	GCS(Before hospitalization)	Current state/GCS	MCS/UWS
1	M	3	Dead /-	UWS
2	M	5	Dead /-	
3	F	5	Dead /-	
4	M	3	Dead /-	
5	M	4	deep coma /4	
6	M	6	deep coma/?	
7	F	5	Can be ordered/15	MCS
8	M	3	Self-care Fully/15	
9	M	4	Self-care Fully/15	
10	M	4	Self-care Basically/?	
11	M	?	Self-care Fully/?	
12	M	3	Self-care Fully/?	

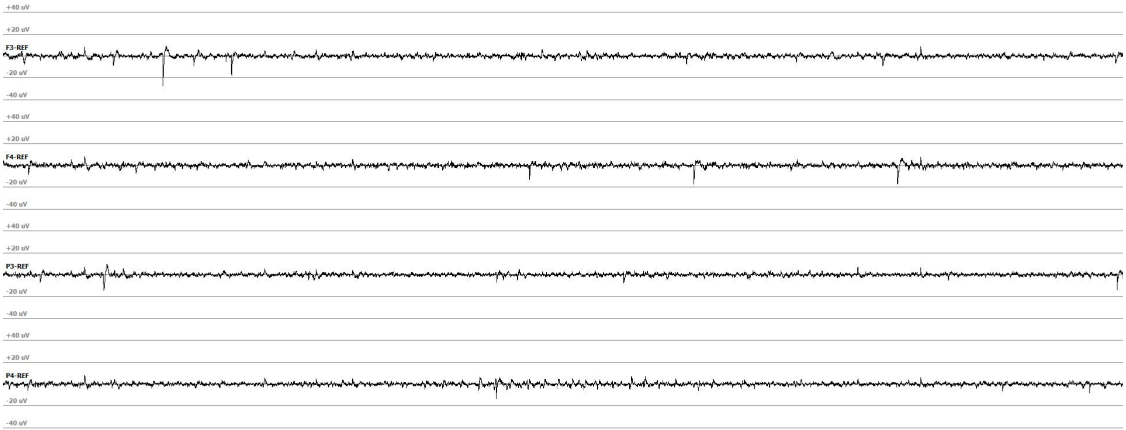
The data comes from Nicolli's acquisition and acquisition system, which contains 4 channels of EEG data (F3, F4, P3, P4). The sampling rate is 250Hz or 125Hz due to system settings during the acquisition process. In this thesis, it is uniformly set to 125Hz for analysis.

3.2 Features analysis

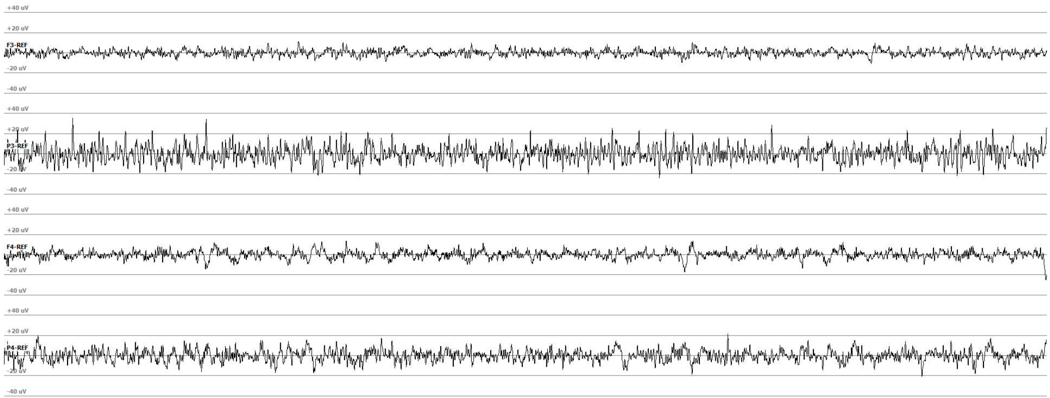
Feature analysis of EEG signals is of great significance for building a suitable CNN network. Different network structures have a different emphasis on the extracted features, and their prediction results will also be different. For EEG signals, this article mainly analyzes its characteristics from the time domain and frequency domain.

3.2.1 Time-domain features

EEG signals waves of patients with UWS and MCS are show in Figure 3.1. As can be seen from Figure 3.1, the EEG of patients with micro-consciousness has a larger amplitude compared with those of plant patients. It also exhibits the characteristics of non-stationary random signals in the time domain. The EEG amplitude of plant patients is very low. Some patients' EEG is only 0 to 10μV, and the EEG activity is very inactive, and the EEG of plant patients has always maintained a very low amplitude.



a) EEG with UWS



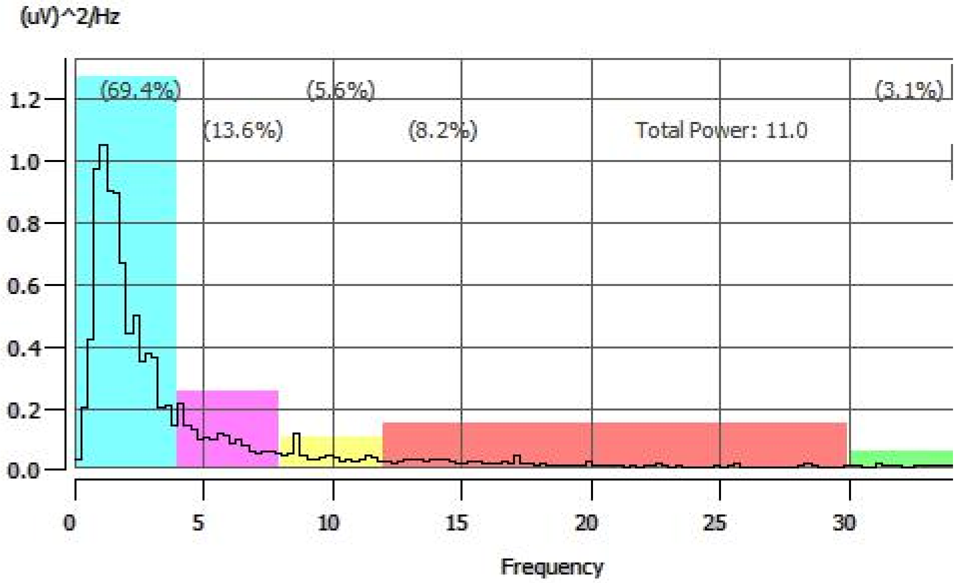
b) EEG with MCS

Figure 3.1 Sample signals from two selected patients.

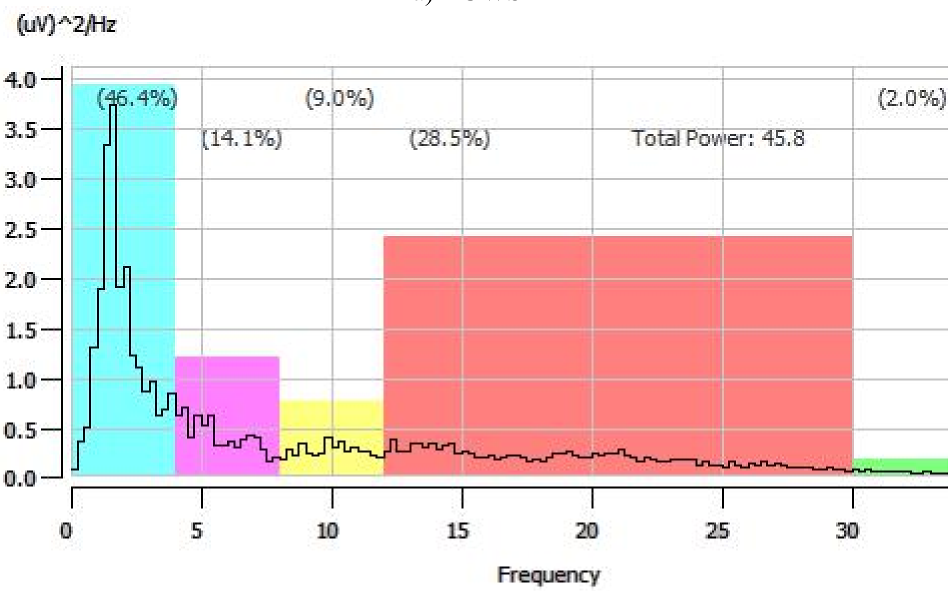
Through comparison, it can be found that the EEG signals of patients with different consciousness levels have apparent differences in the time domain characteristics, and the EEG signals of patients in UWS are smaller than those in MCS in terms of mean and variance.

3.2.2 Frequency domain features

Electrophysiological signals usually show very complex characteristics, which makes it difficult for us to find the characteristics of the signal directly in the time domain. Although the EEG signal of most patients varies significantly in time domain characteristics with different levels of consciousness, the difference in some patients is not apparent, so it is necessary to analyze the characteristics of the signal from the perspective of the frequency domain. Especially for complex physiological signals like EEG, we can better observe the signal characteristics in the frequency domain, the frequency domain waveforms of two patients.



a) UWS



b) MCS

Figure 3.2 EEG signal in Frequency domain

From the above Figure 3.2, we can find that there is a big difference in the frequency components of the EEG of UWS patients and MCS patients, and there are also apparent differences in frequency band energy. Among them, the total power of UWS patients is 11, and the MCS is 45.8.

The main components of normal people's EEG are mainly slow waves. Mainly include δ wave (1-3Hz), θ wave (4-7Hz) α wave (8-13Hz), β wave(14-28Hz) [68]. Figure 3.3 shows the state of the EEG signal measured in the frequency domain under an clear state for sleep research. Between UWS and MCS patients, each frequency band component has some difference, which is mainly manifested in the power spectral density and the proportion of each frequency component.

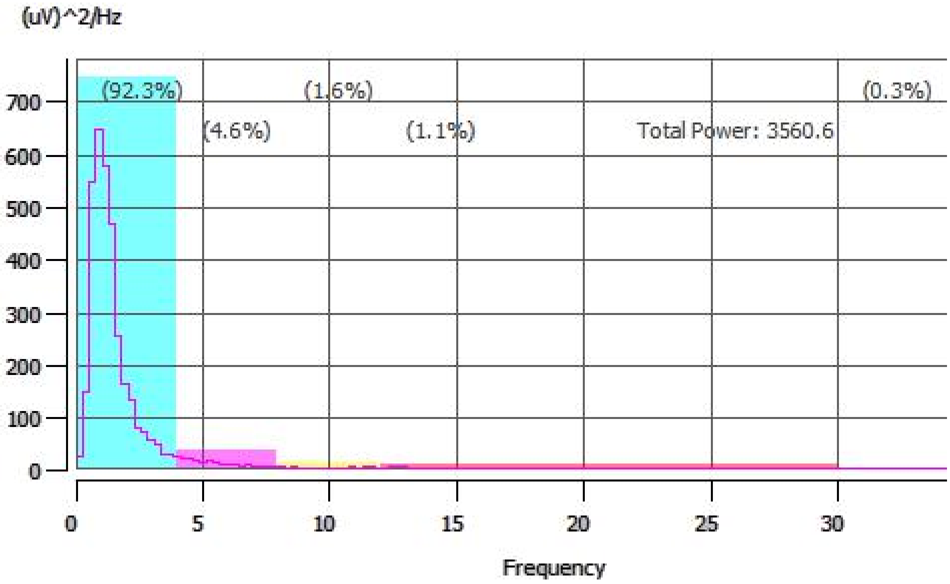


Figure 3.3 EEG sample signal from a person with nominal neural conditions.

The above are just a few examples of representative EEG waveforms and do not represent the EEG of all DOC patients. Each patient has different manifestations of EEG signals due to differences in disease, age, gender, and the way of signal collection. Although the EEG amplitude of most UWS patients is smaller than that of MCS patients, there are also cases where the EEG amplitude of UWS patients exceeds that of normal people. For example, subject 6 patients underwent bone flap surgery on both sides of the brain. The EEG signal amplitude is slightly larger than that of a normal person's EEG. This thesis considers these external factors comprehensively and does not include such patients as the research object.

3.3 1D-CNN for EEG signal

3.3.1 Network build

For DOC patients, EEG signals in most areas of the brain have not much difference. And the EEG signal at F3 in the data set provided by Huashan Hospital has the best quality. Thus, this thesis mainly considers the EEG at the F3 position and builds a network model based on a single channel EEG signal. Since the EEG signal is a one-dimensional signal, in order to analyze characteristics of the EEG signal of DOC patients in time-domain, this thesis first builds a one-dimensional network structure. The specific network structure is shown in the figure3-4. The input layer is an EEG signal with a length of 10s and a sampling rate of 125Hz. And then go through the first convolutional layer, the size of the convolution kernel is 1x32, and the size of the convolution kernel is related to the features you want to extract. Because the EEG signal itself is relatively complex. Thus, selecting a larger volume allows the convolution kernel to have a larger convolution field of view to obtain the features of the signal. In the subsequent convolution layer, the convolution kernel is gradually reduced to retain the features extracted from the previous layer as much as possible to avoid feature loss. After three layers of convolutional layers, the network completes feature extraction, and then these features are expanded and connected to the fully connected layer to optimize the weight of each feature, and finally complete the assessment of the level of consciousness of DOC patients.

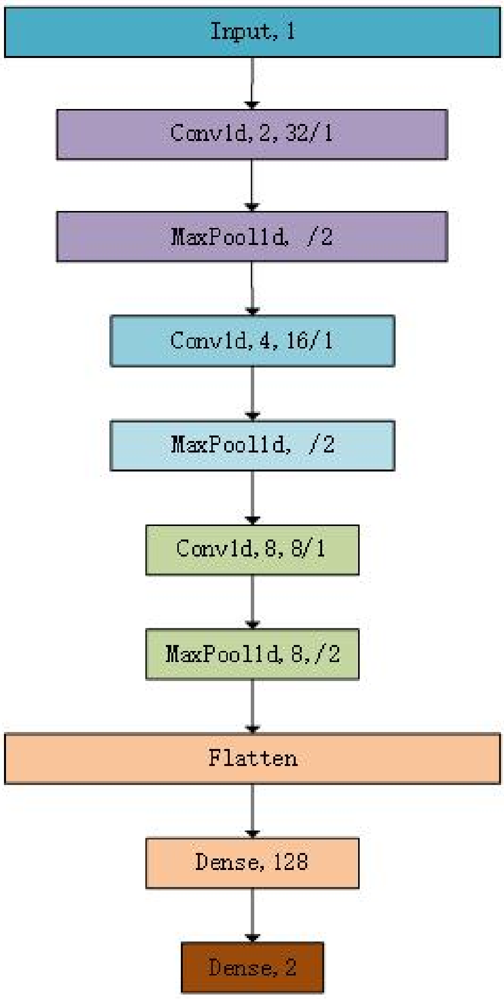


Figure 3.4 1D-CNN Network

3.3.2 Preprocessing and data selection

preprocessing

After building the network, the steps followed in the experiment in this article are as Figure 3.5. In image processing, clear image data can often be obtained, but noise cannot be avoided in the signal acquisition process in electrophysiological signals. Therefore, to get a cleaner signal, it is necessary to filter the signal. In addition, the human body's EEG signal's effective components are mainly distributed between 0-30Hz, but the acquisition rate in the actual process is often high, and reach 1KHz in this system. Down-sampling the signal helps reduce the training time, reduces redundant information, and improves network training accuracy. After that, the signal may still contain unusable data, which requires further screening of the data. Finally, the filtered data is sent to the trained network to get the final prediction result.

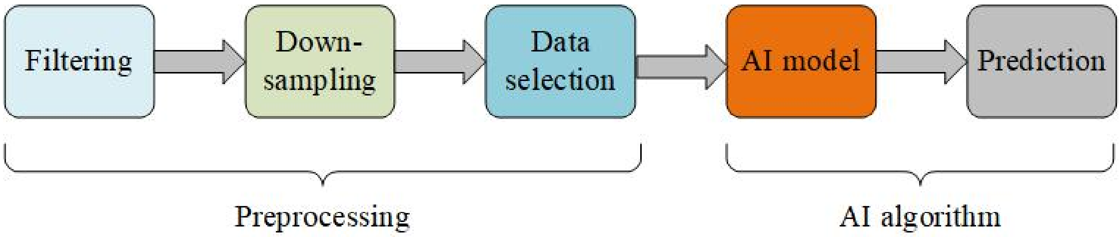


Figure 3.5 The flow of experiment

Data selection

The sample used for training in the experiment is an EEG signal with a length of 10s. The original EEG signal needs to be intercepted with a length of 10s. Before sample extraction, the signal needs to go through a high-pass filter with a cut-off frequency of 0.5 Hz. Since the sampling rate of the signal is uniformly 125 Hz, it is relatively low, so there is no longer a low-pass filter. For signals containing a lot of 50Hz power frequency noise, a 50Hz notch filter needs to be set separately.

During the collection of clinical data, many environmental factors (patient's position, loose electrodes) will seriously affect the quality of the signal, and cause the EEG signal in some time to be completely out of the ordinary. In order to ensure the accuracy of subsequent experimental results, it is necessary to filter the data, and it is also an indispensable step before the start of the experiment. Peng proposed some excellent data screening criteria [69]. Based on this, this article made the following changes:

1. Gradient criterion: the voltage change between two adjacent points does not exceed 30uV

$$|X[i] - X[i+1]| < 30$$

2. Maximum and minimum criteria: Use a sliding window with a length of 120ms and a step length of 10ms. When the absolution between the maximum and minimum values in the data exceeds 120uV, delete it. Since the sampling rate of the data is 1KHz, and our data sampling rate is uniformly 125Hz, therefore, the size of the sliding window is 25 points, and the step size is 1 point.

$$max(X[i: i+25]) - min(X[i: i+25]) < 120$$

3. Amplitude value criterion: the absolute value of the voltage at all points shall not exceed 100uV.

$$|X[i]| < 100$$

4. Low activity criterion: delete when there is no change in voltage within a period. Specific steps: a sliding window with a length of 100ms and a step length of 10ms is used to view the maximum and minimum voltages during this period. If the difference between the two is less than 1, then this sample is not required. In our data set, a sliding window with 20 points and 1 step is used.

$$max(X[i: i+20]) - min(X[i: i+20]) > 1$$

selection, the number of samples collected from each patient is show at Table 3-2:

From the above Table 3-2. It can be seen that the number of samples selected from each patient is not the same, but these data cannot be used in all. Considering that the samples of each patient are not balanced, if all the data is sent to the neural network, the performance of the network will be biased towards some patients with more samples. However, the data of the neural network is greedy, and the amount of data is too small to achieve the training effect. In this article, we consider that patient samples of subjects 4, 6, 7 are not used in the experiment. Among other subjects, the smallest sample is subject3, and the number of samples is 233. In order to ensure the balance between samples, it is also necessary to select the same number of samples from other subjects.

Table 3- 2 The number of samples for each subject

Subjects	Number of samples
1	506
2	552
3	233
4	54
5	3825
6	187
7	171
8	4290
9	2746
10	3237
11	1407
12	2243

Experiment setup

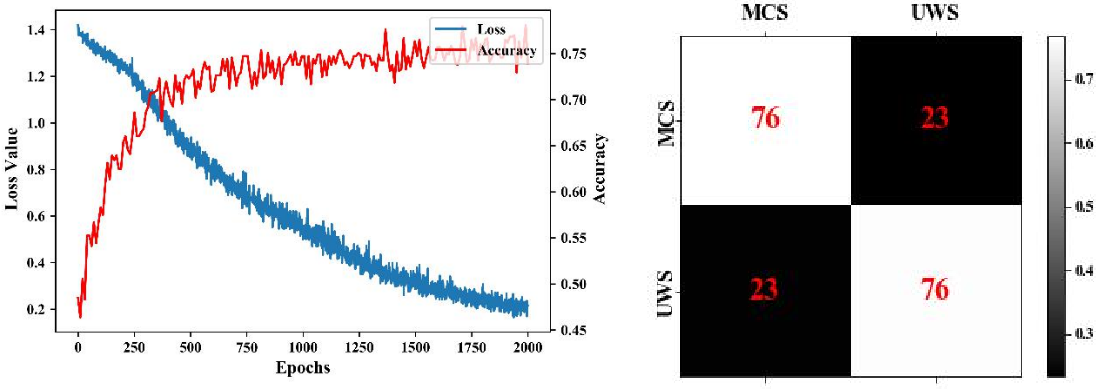
The experimental environment is based on Windows10_X86(X64) operating system, the processor is Intel(R) Core(TM)i5-9600K CPU@ 3.70GHz 3.70GHz, the memory is 16GB, the deep learning framework of CNN is PyTorch, the learning framework is relatively simple, and Have a high training speed, an active community, and rich, open-source documentation.

Table 3- 3 Parameter Setting in 1D-CNN

Phase	Parameter Name	Value
Training	Bias	0
	Activate function	ReLU
	Loss function	Softmax
	Epochs	2000
	Learning rate	0.001
	Batch Size	100
	Dropout rate	0.5
	Optimizer	Adam

Result analysis

Before training, the data set is randomly shuffled to ensure the randomness of the data set. This article divides the training set, and the validation set at a ratio of 1:1 and needs to balance the number of training samples in each category. The changing trend of the loss function and the test results of the verification set are as Figure 3.6.



a) The trend of loss function

b) Confusion matrix on validation set

Figure 3.6 Results of 1D-CNN on evaluating the level of DOC

In the training process, the loss function gradually decreases with the depth of training. When the epoch reaches 500, the value of the loss function begins to fluctuate wildly. That is because the data set in this thesis is relatively small. If there are more data in the future, this situation will be improved. From the results of the test set, the accuracy of the test set has reached about 75%, and the result is outstanding. It shows that our network can distinguish UWS and MCS patients well.

Secondly, the network is verified by cross-validation. Under the structure of this one-dimensional convolutional neural network, the data of one patient is used as the test set, and the other patient is used as the training set to verify the reliability of the network. The experimental results as Table 3- 4:

The result shows the average accuracy is 0.78, that is a good result based on this dataset. However, the network predicts subject 5 almost entirely wrong. That shows EEG signal of subject 5 is really like other MCS patients, and EEG signals in patients with impaired consciousness vary significantly among individuals. Thus, this thesis considers 2D-CNN to solve this problem.

Table 3- 4 The results of Cross-validation

Subject	Accuracy
1	0.55
2	0.73
3	0.88
4	-
5	0.99
6	-
7	-
8	0.69
9	0.53
10	1.0
11	0.62
12	1.0
Average	0.78

3.4 2D-CNN with STFT

3.4.1 STFT introduction

In the analysis of electrophysiological signals, the spectrogram of the signal contains more signal features, and CNN convolutional neural networks are commonly used in image recognition problems, which have a perfect effect on extracting image features. Many researchers also try to transform the signal from the time domain to the time-frequency domain, combined with the CNN convolutional neural network and use the method in the image recognition analysis to classify the time-frequency image.

Fourier transform is widely used in data science, signal processing and other fields. Through Fourier transform, the signal can be transformed from the time domain to the frequency domain, to get its frequency domain characteristics.

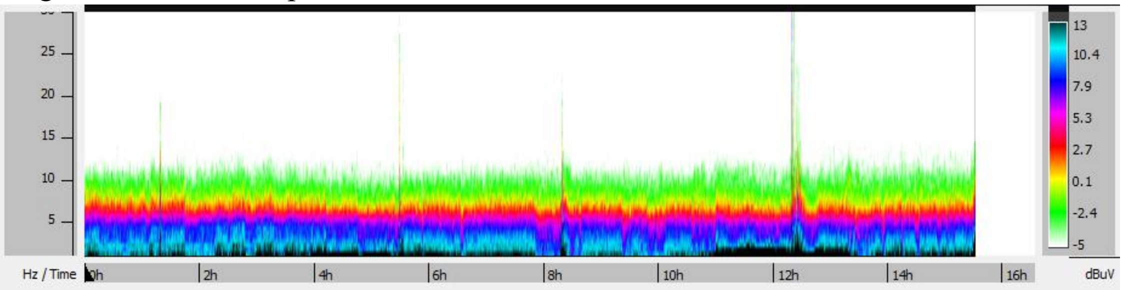
$$X[k] = \sum_{n=0}^{N-1} x[n] e^{-j\left(\frac{2\pi}{N}\right)kn}, (0 \leq k \leq N-1)$$

Which $X[k]$ is the frequency coefficient of the time series $x[n]$ after Fourier transform.

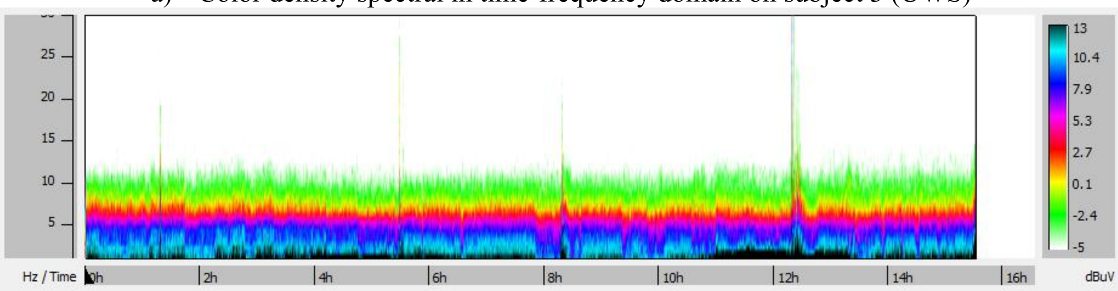
In practical applications, the EEG signal will be recorded continuously for a long time, and the transformation of the EEG signal over time cannot be understood from the frequency domain alone. The short-time Fourier transform (STFT) solves this problem well. The main idea is to transform a long non-stationary random process into a series of short-term random and stationary signals.

$$\mathrm{STFT}\,(t,f)=\int_{-\infty}^{+\infty}x(\tau)h(\tau-t)e^{-if\tau}d\tau$$

Which $h(t)$ is a short time window function, and the result reflects the trend of signal x with time t and frequency f. Because the STFT transform allows us to observe the EEG signal in the time domain and frequency domain, this means that more features can be obtained from it. The following figure is the power density map with subject 3 and 9 after STFT. And the segment length is the 30s, the block length is 2s, the overlap is 80%, and the window function is Kaiser2.



a) Color density spectral in time-frequency domain on subject 3 (UWS)



b) Color density spectral in time-frequency domain on subject 9 (MCS)

Figure 3.7 EEG signal with STFT

3.4.2 Data preprocessing

In order to realize continuous monitoring, the time domain signal needs to be sliced. This thesis uses the 10s length EEG signal and performs STFT on it to extract a sample. The results are as Figure 3.8.

Compared with the one-dimensional time-domain signal, after passing through the STFT, the signal features are more apparent, and more features can be extracted from it. At the same time, as the signal is transformed from one-dimensional to two-dimensional, the neural network built must be adjusted accordingly. The previous one-dimensional convolutional layer needs to be changed to a two-dimensional convolutional layer, and the size of the convolution kernel needs to be adjusted accordingly.

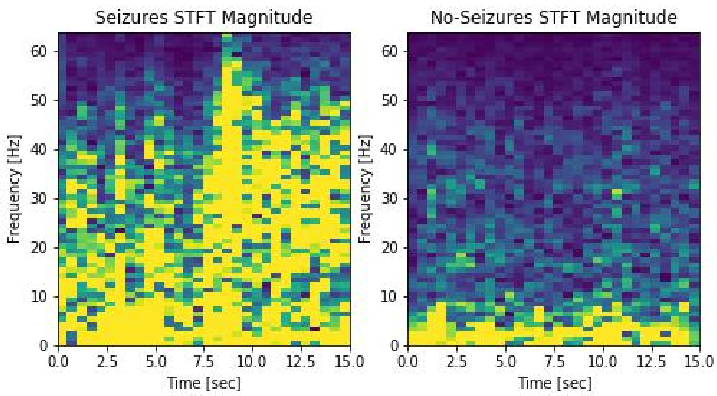


Figure 3.8 The results after EEG through STFT between UWS and MCS

This thesis uses Python's third-party toolkit Scipy, which has powerful signal processing functions. By calling the API interface and setting appropriate parameters, the signal can be easily converted between the time domain and frequency domain. In the general neural network-based image classification issue, the input is RGB three-channel image data. However, after the one-dimensional EEG signal undergoes the STFT, only get a single-channel two-dimensional array. That is different from image processing.

3.4.3 2D-CNN model

The basic network structure used in this thesis is as follows:

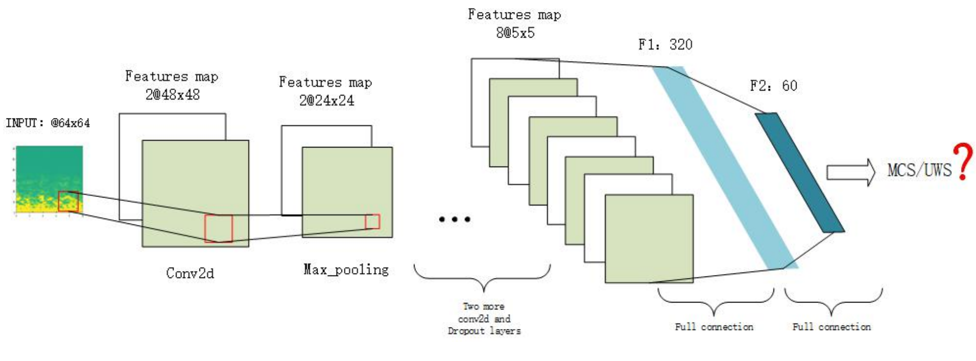


Figure 3.9 CNN + STFT model

This neural network has a relatively simple structure and contains fewer parameters, which speeds up the training process. Also, as an exploratory attempt, this article mainly analyzes the possibility of using deep learning to assess the level of consciousness of DOC patients. After many experiments by setting different network parameters, an

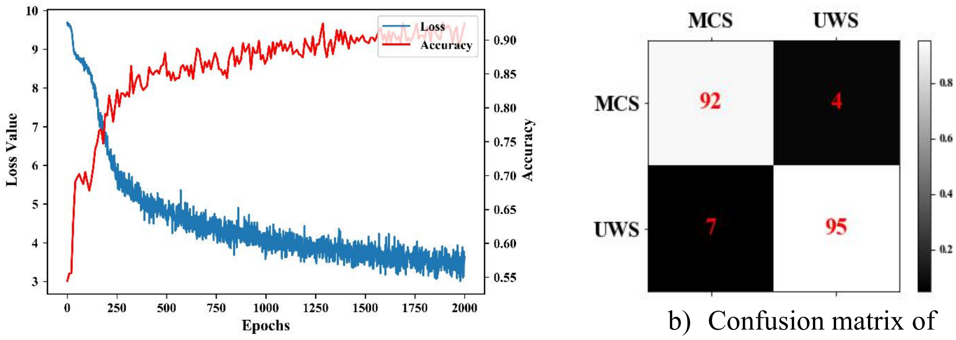
optimal result can be achieved by setting the following parameters.

Table 3- 5 Parameter setting of 2D-CNN structure

Layer Name	Parameter Setting
Conv1	Conv2d(1, 2, kernel_size=(5, 5), stride=(1, 1))
Conv2	Conv2d(2, 4, kernel_size=(3, 3), stride=(1, 1))
Conv3	Conv2d(4, 8, kernel_size=(3, 3), stride=(1, 1))
Dropout	Dropout(p=0.3, inplace=False)
FC1	Linear(in_features=160, out_features=32, bias=True)
FC2	Linear(in_features=32, out_features=2, bias=True)

3.4.4 Training and result analysis

There is no significant difference in the parameter setting during the training process, which is consistent with 1D-CNN. After 2000epochs training, the relevant results are shown in Figure 3.10:



a) The trend of Loss function

b) Confusion matrix of Validation set

Figure 3.10 The result of 2D-CNN

Cross-validation is a statistical verification method, which is often used for model selection and analysis of model stability. The main idea is to group the original data, use part of it as a training set to train the network, and the other part as a validation set to verify the network. The K-fold cross-validation method is to extract one group from all groups in turn as the test set, and the others as the training set to verify the network performance. This thesis selects 9 valid subjects in the original data set. The verification results obtained based on the K-fold cross-validation method are shown in Table 3- 6. It is not difficult to find that the network performs well in most subjects, except for subject 5. Its overall accuracy rate reaches 82%. If not involved in subject5, the overall accuracy rate reaches more than 94%.

Table 3- 6 The result of Cross-validation

Subject	Accuracy
1	0.99
2	0.81
3	0.96
4	-
5	0.03
6	-
7	-
8	0.94
9	0.97
10	0.84
11	0.97
12	0.90
Total	0.82

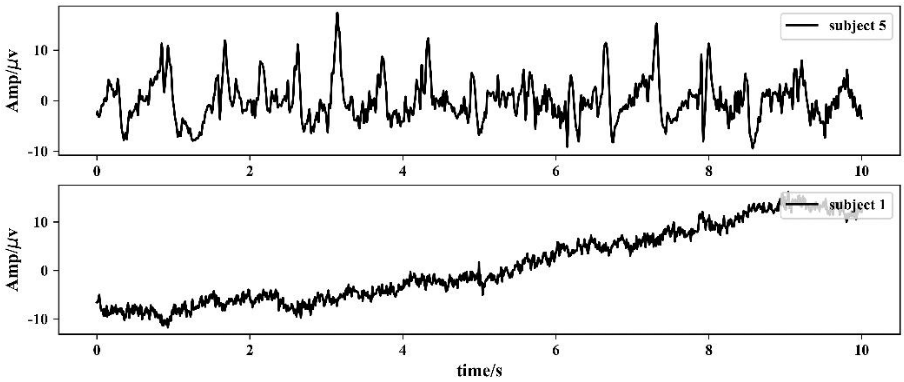


Figure 3.11 EEG of subject 5 and subject 1

After many experiments, it can be found that the use of 2D convolutional neural can get more accurate results than 1D network. This shows that after the EEG signal is time-frequency transformed, CNN can extract more comprehensive features. Especially when dealing with complex physiological signals like EEG, how to get clearer features is the key to solving the problem. During the experiment, we also found some special cases in which the EEG of subject5 could not be predicted correctly in Figure 3.11, which indicates that different patients have large differences in the performance of EEG, and even show opposite characteristics. This increases the difficulty of identifying such patients. This is also one of the directions of subsequent research.

3.5 Chapter summary

This chapter mainly describes how to use CNN to assess the level of consciousness of DOC patients automatically, and analyzes the different manifestations of EEG signals in UWS and MCS patients. Moreover, based on the EEG signal to build a suitable deep learning network model, combined with the data set provided by Huashan Hospital, we can preliminarily reach a conclusion, there are some differences between the EEG of UWS and MCS patients. The adopted CNN model has a high recognition accuracy rate for UWS and MCS. As an auxiliary diagnosis, it can help doctors judge the condition more accurately, and its accuracy has been higher than the average level of judgement by clinicians.

4 Algorithm research based on epilepsy recognition

Epilepsy is one of the common diseases in the world [70]. The study of epilepsy is one of the hot topics nowadays. Finding epileptic seizures in time is helpful for timely treatment. At present, scholars around the world have proposed many excellent methods for epilepsy monitoring, but there are relatively few clinical applications. This chapter combines clinical data to analyze the performance of these methods.

4.1 Characteristics

Compared with DoC patients, the EEG signal of epilepsy patients has more obvious amplitude changes in the time domain. Some experienced doctors can also make more accurate judgments. However, clinically, epilepsy is manifested in many types, and there are some differences in EEG between individual patients. How to better analyze and judge is also the problem to be studied in this article. This thesis also uses the open-source database provided by CHB-MIT [71] and the clinical data about epilepsy collected by Huashan Hospital (Shang Hai, China) to analyze the possibility of deep learning methods in clinical applications.

4.1.1 Time-domain characteristics

1) CHB_MIT dataset

The above picture is from the CHB-MIT data set. The patient's EEG changes before and after the seizure. The left side of the red line is the state of epilepsy without a seizure, and the right side is the state of the epileptic seizure. It can be seen that the amplitude of the EEG signal increases significantly during a seizure, and contains some low-frequency components. Moreover, the signal characteristics are more apparent, and the EEG has no obvious noise signal.

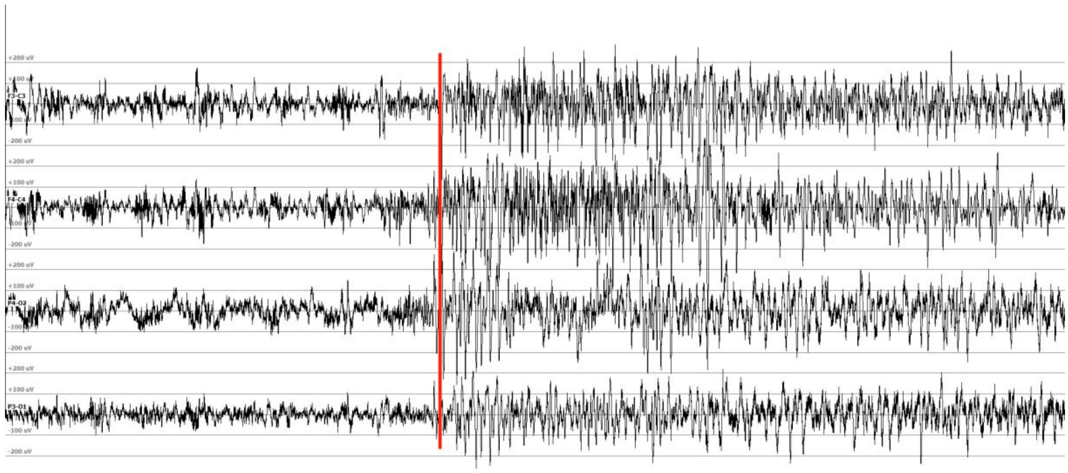


Figure 4.1 The left of red line is Normal EEG and the right of red line is Seizures

This thesis uses the public data set CHB_MIT provided by Boston Children's Hospital. The dataset contains 24 cases which all the EEG signals are continuously sampled and recorded (there will be a short gap due to hardware reasons). Each case has not less than 23 channels EEG signals that were sampled at 256 sampling rate. We select 8 channels (FP1-F3, F3-C3, C3-P3, P3-O1, FP2-F4, F4-C4, C4-P4, P4-O2) EEG signal according to the acquisition location and importance of the EEG signal, And Downsample the data with 128 sampling rate since the useful EEG signals are concentrated in the low-frequency region. That can help reduce redundant information.

2) Huashan dataset

Compared with the EEG of the standard data set, the EEG data collected clinically contains much noise, and the signal quality cannot be virtually guaranteed. In order to further verify the clinical reliability of the artificial intelligence algorithm, this article is based on Fudan University. The clinical data of the affiliated Huashan Hospital has been compared and analyzed. The following is a sample of 10 patients from Huashan Hospital.

Several patients are shown in Table 4- 1. Different from other CHB-MIT data sets, in this clinical data, all epilepsy patients are accompanied by seizures throughout the data recording process, and each epilepsy patient suffers from different diseases.

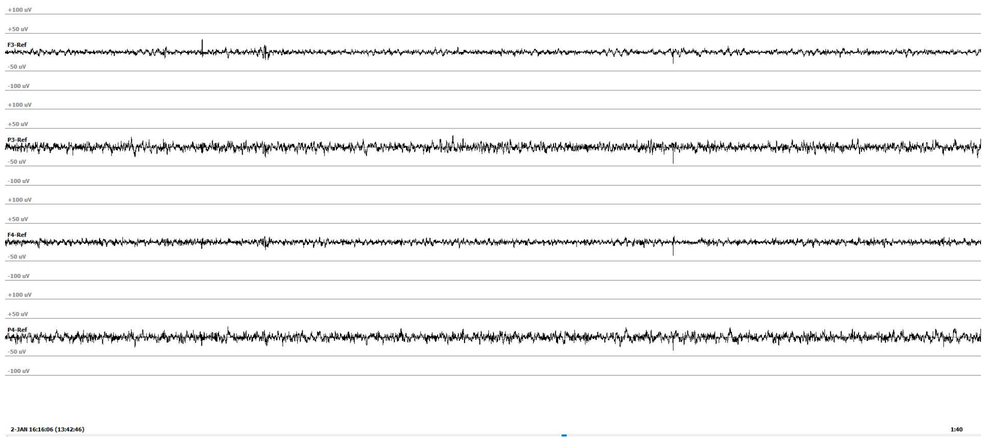
Table 4- 1 The information of patients from Huashan Hosptial

Seizures (red): subjects 1–5; No-seizures (blue): subjects 6–10

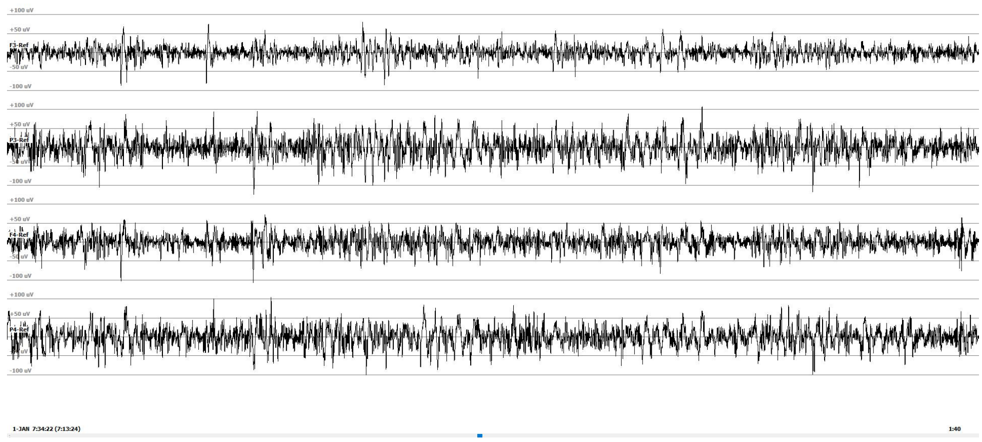
Subject	Gender	Age	Disease description
1	M	81	Subdural hematoma; uremia; hypertension; secondary epilepsy
2	M	24	Viral encephalitis; pneumonia; secondary epilepsy
3	F	30	Ischemic hypoxic encephalopathy; secondary epilepsy
4	F	28	Brain abscess; secondary epilepsy
5	M	70	Autoimmune encephalitis; secondary epilepsy
6	M	54	Ischemic hypoxic encephalopathy; pneumonia
7	M	68	Viral encephalitis; pneumonia; buttock abscess
8	M	76	Extensive subarachnoid hemorrhage; brain herniation; pneumonia
9	M	54	Brain stem hemorrhage; pneumonia; liver cirrhosis
10	F	45	Intracranial space (possibly lymphoma); hydrocephalus; pneumonia

The above figure shows two cases of clinical EEG data from Huashan Hospital. It is not difficult to find that the EEG signals are still quite different between the two types of patients in time domain.

Like the collected EEG data of DOC patients, this data set also contains a large amount of abnormal data. Most of the time, these are caused by changes in the patient's position, natural loosening of electrodes, falling off, and environmental power frequency interference. For this reason, this thesis automatically filters and judges the data for theis situations.

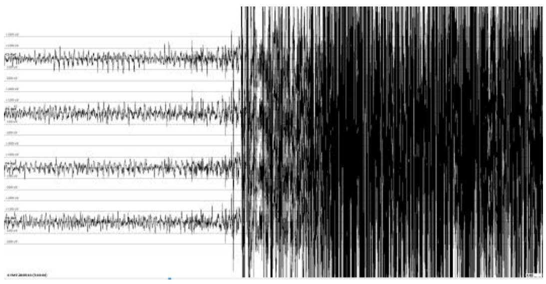


a) No-Seizures

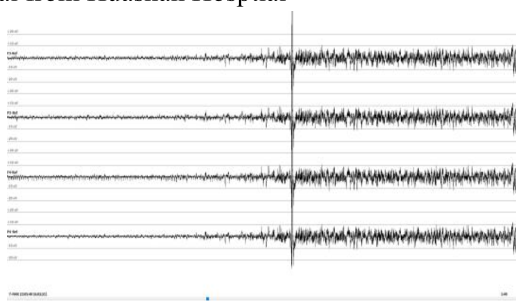


b) Seizures

Figure 4.2 EEG signal from Huashan Hosptial



a)

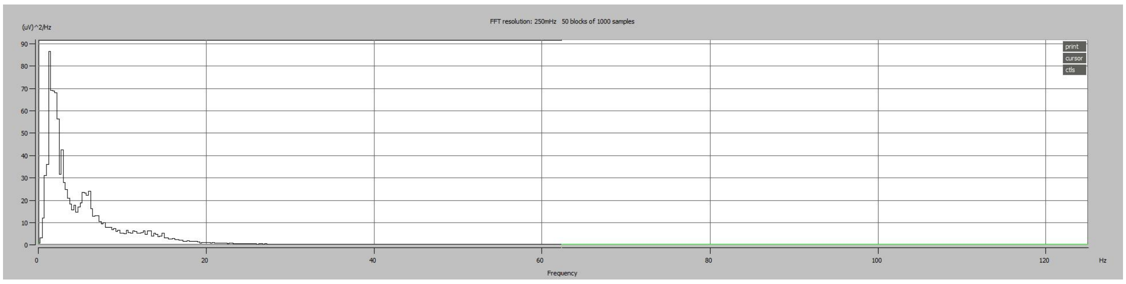


b)

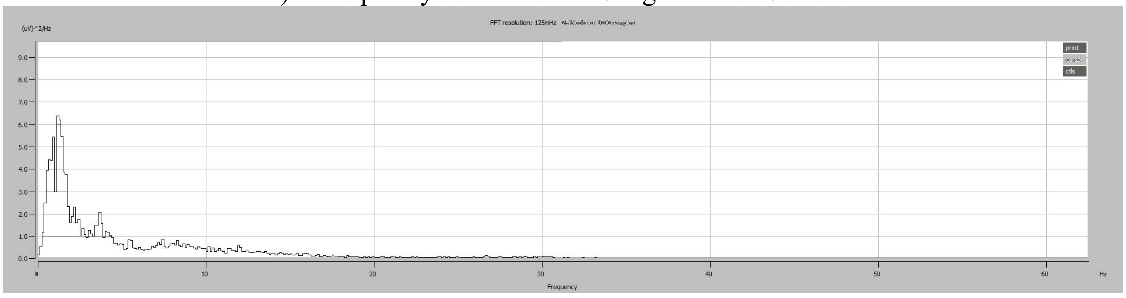
Figure 4.3 EEG data with noise

4.1.2 Frequency domain characteristics

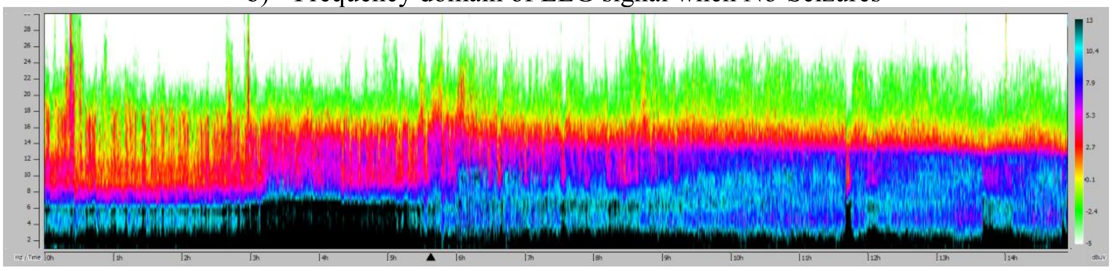
In the frequency domain, patients with epilepsy also have apparent changes. Through analysis and comparison, the EEG of patients with Seizures is higher in low-frequency components. When the patient has no seizures, the EEG tends to be stable, and the low-frequency component is small.



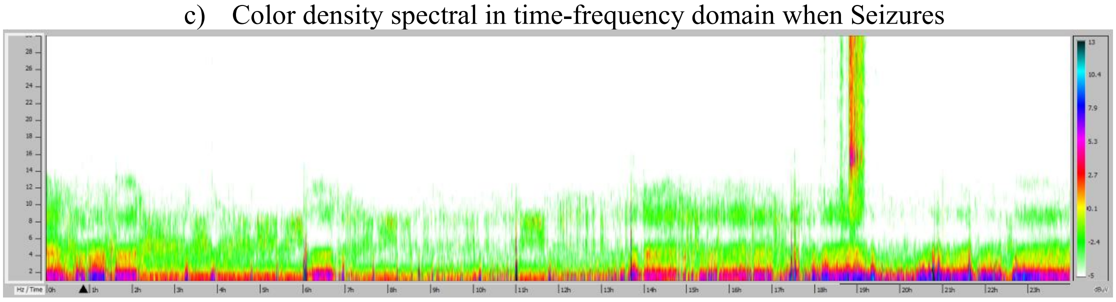
a) Frequency domain of EEG signal when Seizures



b) Frequency domain of EEG signal when No-Seizures



c) Color density spectral in time-frequency domain when Seizures



d) Color density spectral in time-frequency domain when No-Seizures

Figure 4.4 Frequency characteristics of EEG signal from Huashan Hospital dataset

In Figure 4.4 (c), the low-frequency component of the patient remains high consistently throughout the recorded period, the epileptic seizure is persistent, and the brain nerve cells are in a state of abnormal discharge. In Figure 4.4 (d), the patient has no seizures, and the power spectral density is low throughout the period, which is a normal state.

In the clinic, epilepsy is divided into different types. The next step is the diagnosis of epilepsy type, including focal epilepsy, generalized epilepsy, combined generalized, and focal epilepsy, and also an unknown epilepsy group. This thesis will not do in-depth research on a specific type of epilepsy, only to determine whether epilepsy has seizures.

4.2 CNN with CHB-MIT data

4.2.1 Data preprocessing

CHB-MIT dataset is highly imbalanced because of the short seizures in each record, most recorded seizures last only about 100s or shorter. It will cause a severe lack of samples for seizures, and severe overfitting when training the network with this dataset directly. In order to improve the performance of the model, all the samples contain 15s continuously EEG signals to make the model to extract features easier. Thus, we use over-sampling to sample the seizures data segments. In our experiment, we use 15s sliding window, 3s strides to capture the samples from the seizures data segments. In order to get a useful dataset, the first 5 s and last 5s data of seizures were discarded. Considering the difference of EEG signals between different individuals, like children, elderly or young adults, we sampled data from all the cases and use it to train the model. In [62], the proposed MV-TSK-FS has very high accuracy on a single group that contains one patient's data. The average accuracy of seizures detection is about 98.33 ± 0.18%. However, this model did not consider the difference between EEG signals in different individuals. That makes the model does not have the same performance in other patients. In this thesis, a total of 2118 seizures samples were used. In order to balance the dataset, also randomly capture about 2000 no-seizures samples from all the cases.

4.2.2 Model implement and result analysis

The network was implemented on high-performance AI computing device (NVIDIA Jetson Tx2) with PyTorch. In the training process, the loss function is Cross-Entropy Loss. Furthermore, we use Adam optimizer (learning rate: 0.001) to minimize the loss, training batch is 500, the epoch is 200. Before training the model, we divide the dataset into a training set and validation set, and the training set account for 80% and the rest is the validation set. In each epoch, the training set will be shuffled to avoid overfitting.

In this experiment, this thesis uses three kinds of models to verify our system. In Figure 4.5, From regular CNN model to a more complex model, we compare the performance of them. For regular CNN model, that has a simple architecture with three convolutional layers and two fully connected layers. The result shows that there has a good performance and achieve the accuracy, sensitivity and specificity of 92.22%, 91.65%, 92.79%. Considering the different kernels of different sizes have different perception horizons. Thus, we use big kernels to extract big features and use small kernels to extract small features. Then make the features together and make a classification. The result still has a good accuracy of 91.86%. For EEG signals, we usually get more information on the frequency domain. Thus, we use STFT method to transform the EEG signals from the time domain to time-frequency domain firstly, then build 2D CNN model to extract the features. in this method, we found that the performance of the model has been improved a little. The performance of Deep Learning is positively correlated with the quality of the dataset. Many factors include data collection systems, the ways of sampling data, preprocessing will influence the performance of the model a lot.

Table 4- 2 The performance of different models

Models	Accuracy	Sensitivity	Specificity
Normal CNN	92.22%	91.65%	92.79%
CNN with different kernels	91.86%	93.88%	89.70%
CNN+STFT	92.71%	91.30%	94.30%

Through the above experimental results, it can be understood that the CNN network has a relatively good effect on the extraction of EEG signal features. On the other hand, the results also reflect that the quality of the CHB-MIT data set is better, and the differences between individual patients are relatively small. Although this has achieved relatively good results, it still needs to be clinically verified.

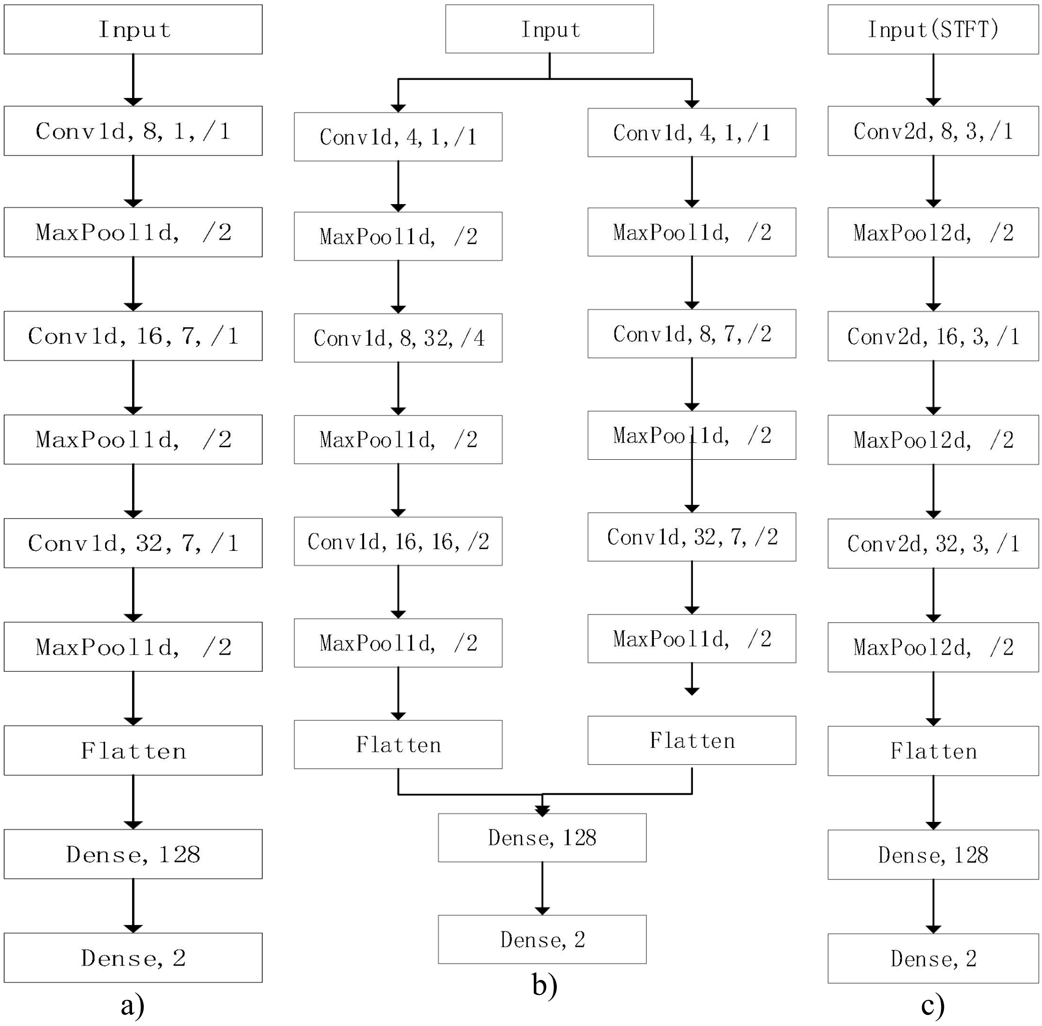


Figure 4.5 (a): normal 1D CNN model with 3 convolutional layers and 2 fully connected layers. (b): model with using different size of kernels in convolutional layers, and combine the features after Flatten. (c): the same frame with (a), the difference is using 2D convolutional kernels in 2D time-frequency domain images from STFT.

4.3 CNN with Huashan dataset

Compared with the assessment of the patient's level of consciousness, related scholars have proposed various models in this regard for the problem of epilepsy, and these models have also made significant progress in epilepsy recognition. However, automated epilepsy monitoring has not been widely used in clinics, and epilepsy monitoring still relies on doctors to judge themselves. This thesis no longer improves the epilepsy recognition algorithm from an algorithm perspective, but combines the actual situation from a clinical perspective, whether these proposed network models are suitable for clinical application. Moreover, give full consideration for several reasons:

1. There is a big difference between the standard data set and the actual collected data. The EEG signal is weak, and it is easy to receive interference from external factors during the collection process, which makes the collected EEG signal and the reference data very different. However, in the process of EEG analysis, a large number of researchers currently use open-source, public data sets as benchmarks to analyze features and establish models through such EEG, which lacks clinical verification.

2. Some of the network models usually have a better effect on some specific data sets. If the data is changed or the sampling rate of the EEG signal has deviated, whether these factors will affect the performance of the network is a question.

4.3.1 Data preprocessing

For the collected physiological signals, in order to ensure that the data has good quality. Preprocessing is an essential step before the data is applied to the network. Same as the method of consciousness disorder analysis in the previous chapter, the data needs filtering to remove noise and unnecessary signals, and then the sampling rate of all patient data is normalized to 125Hz, and the most unqualified ones are removed according to the data screening criteria.

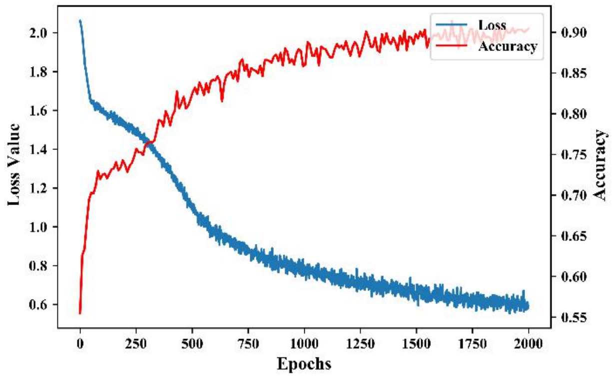
After selecting, the samples of each subject are as follows:

Table 4- 3 samples from subjects

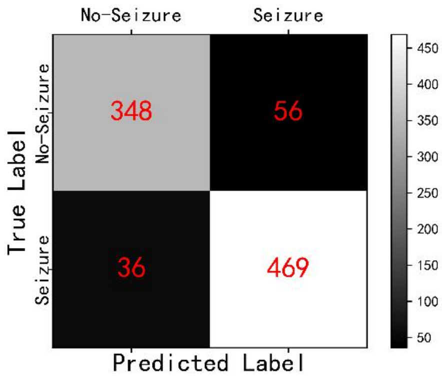
Subject	Number of samples
1	506
2	552
3	233
4	54
5	3825
6	187
7	171
8	4290
9	2746
10	3237
11	1407
12	2243

4.3.2 Experiment setup and analysis

As a comparative analysis, the experimental environment configuration is consistent with the previous environment configuration. The specific configuration is shown in the table. After 2000 epochs training, the loss function change and the confusion matrix on the verification set are shown in Figure 4.6.



a) Loss function and Accuracy



b) Confusion matrix on Validation set

Figure 4.6 The performace of CNN+STFT on Huashan dataset

By comparison, the network built using CNN+STFT has a better accuracy rate, and the recognition accuracy rate on clinical data reaches 89%. Table 4-4 shows the results of its cross-validation, and its average accuracy is 90%.

Table 4-4 The results of Cross-validation

Subjects	Accuracy
1	0.95
2	0.95
3	0.94
4	0.94
5	0.74
6	0.83
7	0.90
8	0.88
9	-
10	0.95
average	0.90

4.4 Chapter summary

This chapter mainly introduces the EEG signal characteristics of patients with epilepsy and analyzes the differences between several commonly used deep learning network models in standard data sets and clinical data sets. Compared with the standard data sets, the network based on clinical data sets. Although the performance is low, it still has a high accuracy rate. The main reason for this factor is the quality of the collected signal. By improving signal processing methods such as data filtering and signal denoising, the detection effect of the network can be effectively improved.

5 Implementation and verification of multi-modal IoT system

5.1 Data visualization and signal analysis software design

5.1.1 Software development platform introduction

The software development platform is based on TX2. As a high-performance AI computing device, its powerful computing capability provides a reliable guarantee for the training of the deep learning network. It is an ideal, embedded development platform. Moreover, TX2 is an ARM architecture, and there are many types of operating systems that support the ARM architecture. With the development of the Internet of Things and artificial intelligence technology, processors based on the ARM architecture have been widely used. This article also conducts software development on this platform and artificial intelligence algorithms Research.

Figure 5.1 TX2 platform

5.1.2 Interface design and software function introduction

The visualization software of the host computer mainly includes the real-time display of the signal. During the development stage, we need to observe the original real-time signal so that we can adjust the hardware system. In actual use, doctors sometimes need to pay close attention to the changes in EEG. The software visualization system designed on TX2 that can display 8-channel EEG waveforms and 2-channel NIRS signals in real-time and can analyze the collected signals in real-time in the frequency domain. It shows as Figure 5.2

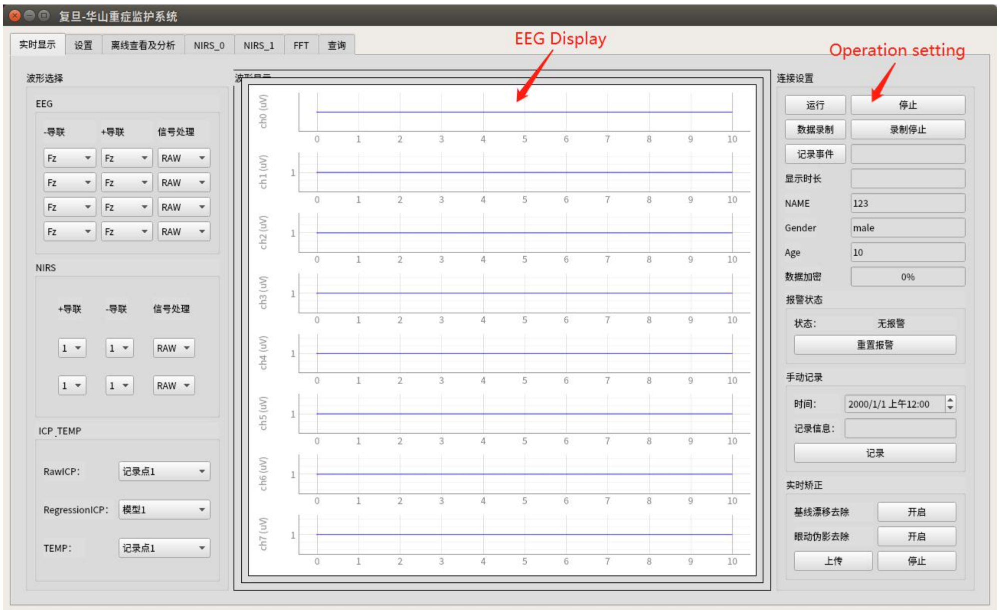


Figure 5.2 GUI design

5.1.3 Software implementation and development

This thesis develops and designs software based on Python and PyQt5 [72] according to actual needs and development efficiency in software development. As one of the essential tool languages for data analysis and artificial intelligence algorithm research, Python has a wealthy third-party open-source support library and supports almost all operating systems at present, with strong cross-platform performance. The software developed through Python is available on the Windows Operating system, Linux operating system can run smoothly, with good compatibility. Large third-party libraries significantly shorten the development cycle. Secondly, to be able to portray the signal waveform, a useful graphics development tool is also essential. QT is currently a commonly used GUI design tool, developed by C++, with excellent cross-platform features, supporting numerous operating systems. Its object-oriented development model makes the code reusable very high. That is very friendly for developers. QT has a rich API, and graphics rendering is excellent. Pyqt5 is based on QT. It is the python interface of QT and is an excellent GUI design toolkit.

This thesis limits the frame rate of the signal waveform refresh. Due to the human eye's visual residual characteristics, the number of optical frames per second when people are relaxed is 24 frames per second, and when they are concentrated, they do not exceed 30 frames. Therefore, the number of frames drawn in this article is also limited to 30 frames to ensure that medical staff can have a better observation experience and to reduce the consumption of CPU resources.

Matplotlib has always been a commonly used image drawing toolkit for Python. However, the toolkit is not efficient in drawing real-time signal waveforms. For this reason, this article uses Pyqtgraph, which is more efficient than Matplotlib in a real-time signal drawing.

Visualization software is mainly used by medical staff. The software's friendliness should be fully considered in the design, and the principle of simplicity and convenience should be followed while ensuring that there are rich functions. However, in many cases, simplicity and convenience contradict rich functions and consider the limited ARM computing resources on TX2. The design pattern of the software is also the primary method considered in this thesis.

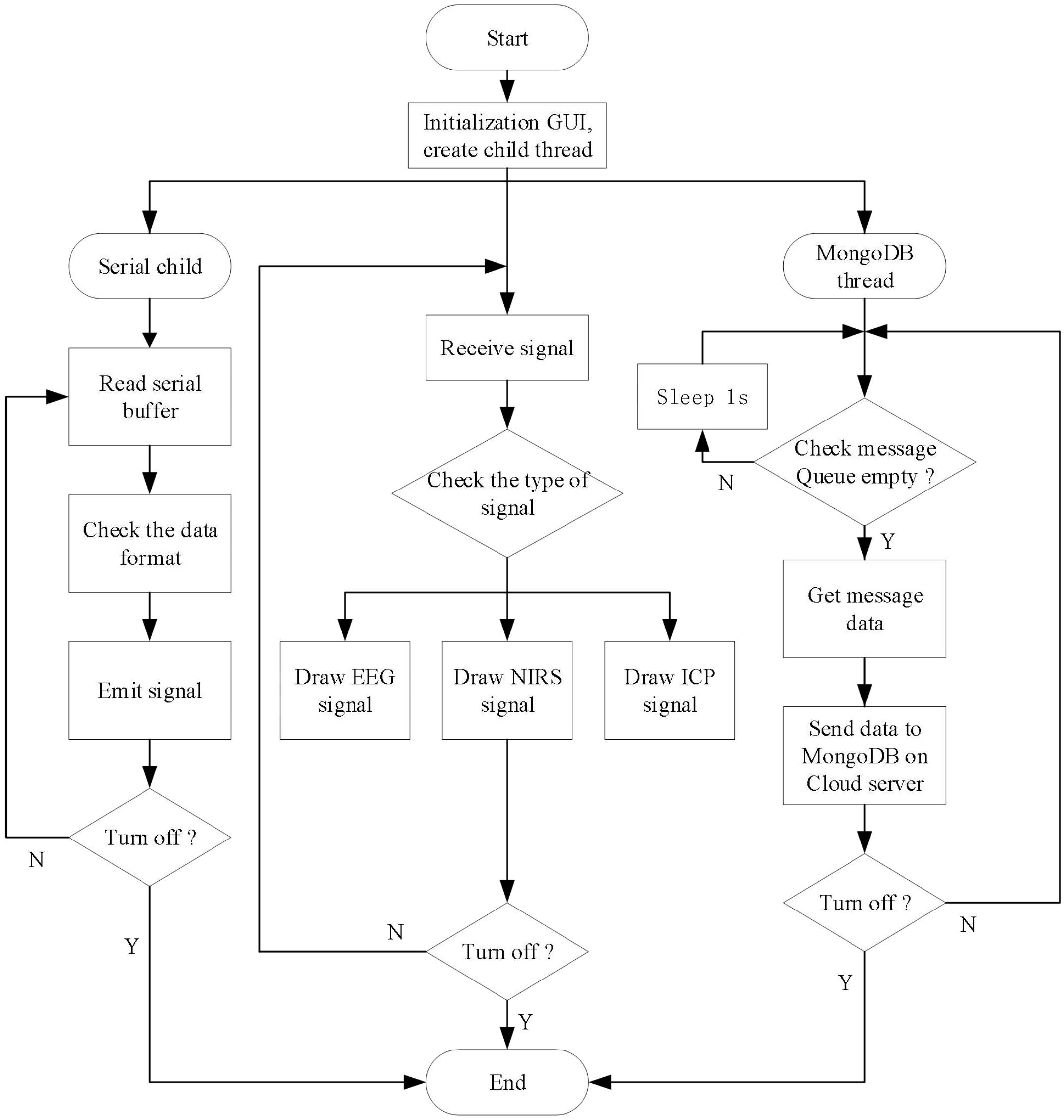


Figure 5.3 The workflow of GUI

In order to obtain a smoother software running experience, multi-threaded programming is often used in the software development process. Multi-threading can improve the efficiency of software operation, allowing multiple module units to execute different tasks at the same time, making full use of the CPU Computing resources. Although multi-threaded programming dramatically improves program operation efficiency and the smoothness of software operation, it also brings many problems. One of the most critical problems is data competition. When multiple threads access the same resource at the same time. It is easy to cause such problems. How to make different threads access the same resource in an orderly manner is a significant problem to be solved in multi-threaded programming.

Different from general multithreaded programming, in the development of GUI software based on PyQt5, PyQt5 provides many multithreaded programming interfaces. By calling these interfaces, this kind of multithreading can be realized very conveniently, and the data communication and data competition between threads PyQt also provide a perfect solution. The signal and slot mechanism is a critical way to solve data communication and data competition. Besides, queues are also a suitable method in some production-consumption model and have been widely used, is a thread-safe data transmission method. This thesis makes full use of these two methods. The software operation efficiency and resource consumption are optimized.

In GUI design, multithreading is inevitable in the development process. In order to make the software run more smoothly, object-oriented and modular programming are the main ideas of development.

5.2 Back-end development based on the cloud server

5.2.1 Django server function introduction

Django is a web framework developed based on python [73], which is widely used in some website applications. The powerful function of Django enables developers to build and deploy complex web applications quickly. Compared with other frameworks based on python development, Django has a very active community, making it possible to find suitable solutions during the development process.

Also, Nginx acts as a high-performance reverse proxy server for connecting clients and servers [74]. When the client initiates a request to the server, it first passes through the Nginx server, then Nginx sends the client's request to the server, and finally returns the result to the client. When the website visits a lot, Nginx can achieve load balancing through the reverse proxy, which is very necessary for developing large-scale websites. When a server is down, Nginx can send the request to other servers to ensure the service's regular operation. Also, Nginx performs well in the case of high connection concurrency.

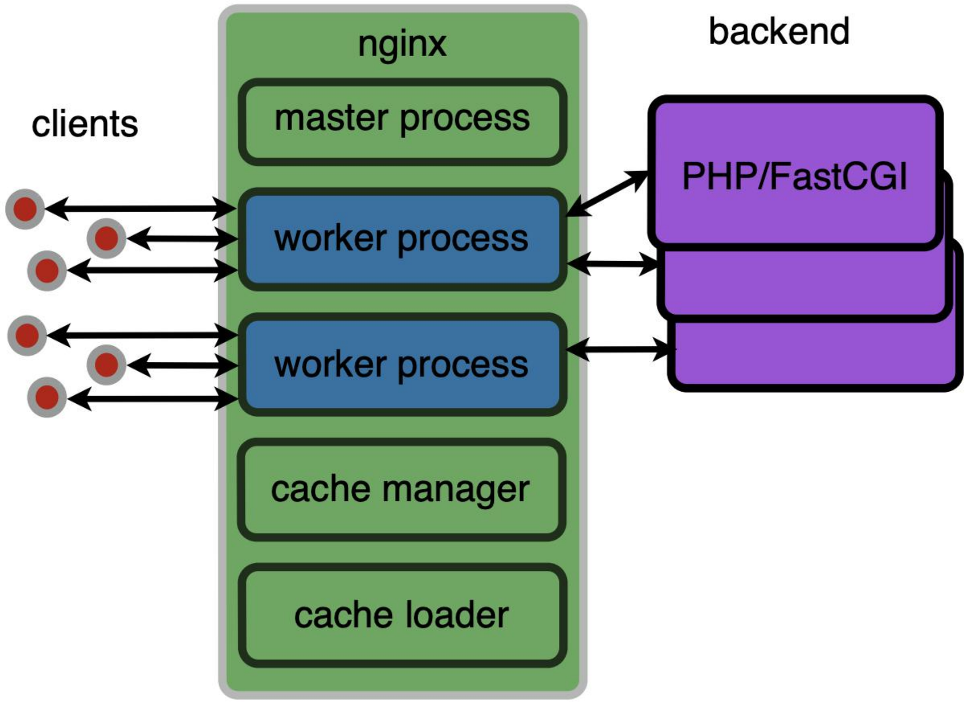


Figure 5.4 Nginx proxy server [74]

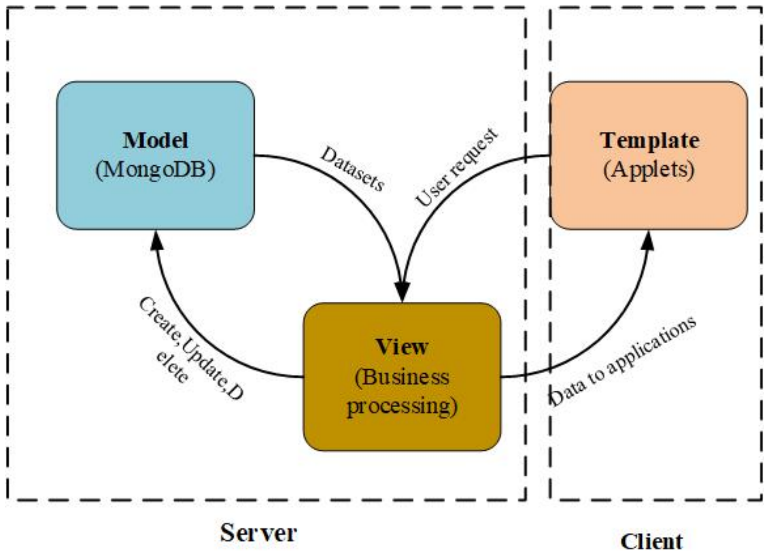


Figure 5.5 The structure of Django (MTV)

Django is a loosely coupled network framework that enables independent data management, design, and business processing modules to complete the system's rapid deployment. The Figure 5.5 shows Django's MTV framework, which is similar to Model-View-Control (MVC). In the MTV framework, Django Templates as a client to request the server and receive the data returned. Model is usually used as an instantiation object of the database to execute specific operations such as inserting, modifying, deleting, and returning it to the View function. The View function is used to process business, establish a connection between the client and the database, and implement the logic functions. Different from the general web application, this thesis is based on WeChat applet development. Thus, Applet as a client to initiate a request to the server. Combined with the above Nginx proxy server, the structure of the system is shown in Figure 5.6.

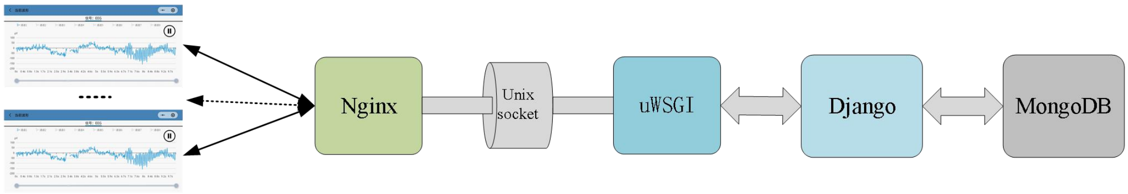


Figure 5.6 Data communication between Applet and Django

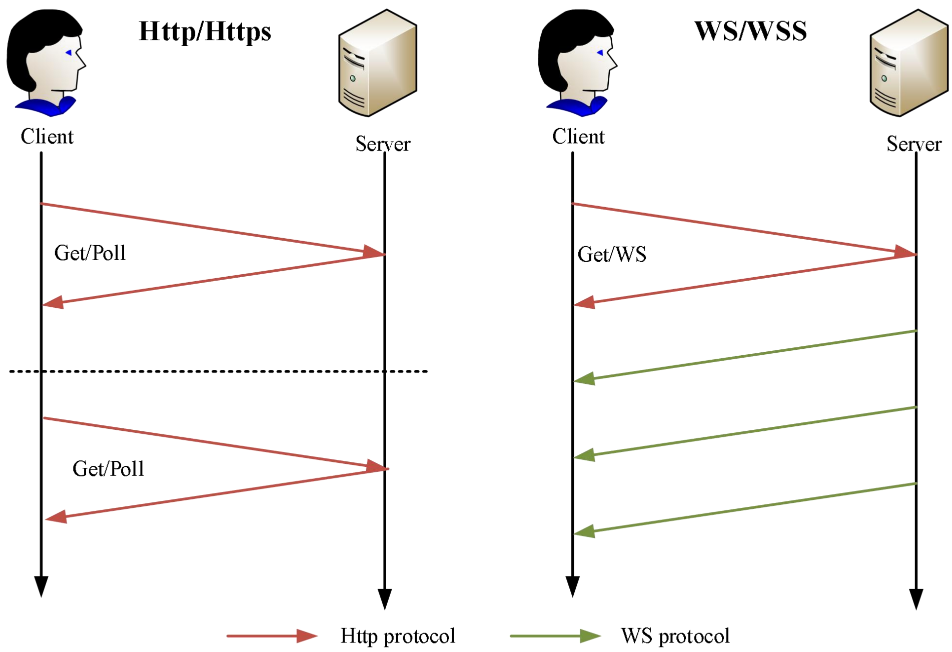


Figure 5.7 Communication based on Http and WebSocket protocol

In order to improve the real-time performance of data transmission and ensure the security of communication, this thesis uses the SSL-encrypted WebSocket (WSS) communication protocol in Figure 5.7. It only requires the client and server to complete a handshake during the data transmission process. Then keep the connection state. Whenever the server data is updated, the server will automatically send data to the client. In the general Http protocol communication method, the client will use a polling method to check whether the server has updated data, which increases network overhead, wastes network resources, and has an unavoidable delay. In this article, considering that the data transmission between the data client and the server is very frequent, and the system has high real-time requirements, a communication method based on WSS will effectively solve it.Server deployment and implementation

1. In order to ensure the security of network communication, the WeChat applet requests to use the communication protocol based on SSL to initiate network requests. Therefore, this thesis applies to relevant domain names and SSL certificates on Alibaba Cloud. After applying, deploy the SSL certificate to the server, the main steps are as follows:

2. Modify the configuration information of Nginx, upload the downloaded SSL certificate and key file to the specified folder. Since the https protocol uses port 443 by default. Nginx needs to listen for client requests on port 443.

```
server {
    listen       443 ssl;
    ssl_certificate "/etc/pki/nginx/server.crt";
    ssl_certificate_key "/etc/pki/nginx/private/server.key";
    server_name : www.chenlin5678.com;
```

Figure 5.8 The port setting on server

In addition, this thesis uses a cloud server. Thus, the cloud server's port 443 makes sure be opened in the security group settings.

允许	1	自定义 TCP	目的:443/443	源:0.0.0.0/0	System created rule.

Figure 5.9 setting on cloud server

3. Modify settings.py in the Django configuration file.

```
SESSION_COOKIE_SECURE = True
SECURE_PROXY_SSL_HEADER = ('HTTP_X_FORWARDED_PROTOCOL','https')
CSRF_COOKIE_SECURE = True
```

Figure 5.10 The configure of Django server

After the environment is configured, the server function needs to be implemented. The Django backend accepts client requests through the view function and provides related services. In order to ensure normal communication between the server and the client, this article also specifies the format of data communication to ensure that the data can be easily interpreted while communicating. How to format the data is an important point to be solved in this article. Considering the dictionary data structure is relatively simple, easy to expand, and has strong readability, this article adopts a data format similar to the dictionary data structure for data interaction. Set the appropriate message field for each message. The specific format is shown in Table 5- 1.

Table 5- 1 The format of message

Message description	Message field	Message type
Patient’s name	P_name	Basic information
Patient’s ID	P_id	
Patient’s disease	P_disease	
Patient’s EEG	P_EEG	Physiological parameters
Patient’s NIRS	P_NIRS	
Patient’s ICP	P_ICP	
....		

The above table lists some necessary message fields. Besides, it also contains some information such as patient's family members, attending doctor information, hospitalization information, Etc., this thesis will not list them all. For the signals of some physiological parameters such as EEG, these signals have a large amount of data and are not suitable for continuous long-term transmission and consider the server's performance and the database. In this thesis, these collected physiological data are stored and transmitted in segments with a unit of 10s.

Table 5- 2 The format of EEG data

Message field	Channel name	Data length /s	Data example
P_EEG	F3_REF	10	{23,34,45,56,54,32...}
	F4_REF	10	{33,35,45,56,54,32...}
	C3_REF	10	{53,34,45,56,54,32...}
	C4_REF	10	{33,34,45,56,54,32...}
	P3_REF	10	{73,34,45,56,54,32...}
	P4_REF	10	{53,34,45,56,54,32...}
	A1_REF	10	{22,34,45,56,54,32...}
	A2_REF	10	{28,34,45,56,54,32...}

5.3 Design and build based on the MongoDB database

Different from general physiological signals, a large amount of data is generated in the process of EEG acquisition. Based on 8-channel EEG, 44Kb of data is generated in 1 second at a sampling rate of 1000 Hz, and EEG acquisition usually takes a long time. Long-term data accumulation will inevitably require better data storage and management method.

5.3.1 MongoDB introduction

MongoDB is an open-source, high-performance, modeless, document-oriented database developed based on C++ [75]. Since MongoDB is text-oriented, it can store text data in JSON format, making it not very strict on the data format during the storage process. It is very suitable for storing large amounts of text data and has a very high query speed. Unlike other types of databases, MongoDB is developed for collections. At present, most databases use tables to store data, while MongoDB uses collections to store data. The stored records are not strictly defined, which means that we customize storage in the stored procedure. Content. Each set has a unique identifier in the database to ensure its uniqueness.

Using python's third-party library Pymongo, it is very convenient to establish a connection between local and the database, operate the database, and accelerate the development process.

5.3.2 MongoDB deployment

During the storage process, we cannot just save the collected data. In order to facilitate subsequent data query and playback of the previous data, the time node information when the data is stored needs to be saved during the storage process.

In order to reduce the number of database visits, the data is stored in a unit of 10s, the serial number is added as the primary key index of the record, the data time node information and user information are added, and a complete data package is constructed, and then the time and the primary key index are used to proceed. Data search and access.

In order to facilitate subsequent database access, this article specifies the format of the data stored in the database collection, and restricts the necessary fields to facilitate subsequent quick search. By limiting the format of data storage, the efficiency of data storage can be improved.


```
{ "_id" : 0, "name" : "zhangsan", "age" : 34, "gender" : "male", "start reco
rding time" : "2020-09-08 13:07:58", "end recording time" : "None", "nirs0 s
tart recording time" : "2020-09-08 13:07:58", "nirs0 end recording time" : "
None", "nirs1 start recording time" : "2020-09-08 13:07:58", "nirs1 end reco
rding time" : "2020-09-08 13:08:10", "nums" : 0, "col_id" : 0 }
>
```


Figure 5.11 Example record from MongoDB

The format of MongoDB data storage is as shown in the figure above, and the database deployed on the cloud server will instantiate the data into memory to ensure data security.

In order to prevent the database from being invaded, this article limits the IP port that the database accesses, and the database is only open to specific IP addresses. Effectively reduce the risk of database attacks by hackers.

5.3.3 System verification

To this point, the design and development of a complete IoT monitoring system has been described. In order to verify the effectiveness of the system, this thesis has conducted various tests on the system.

Signal quality assessment:

This thesis collects EEG signals of normal people under laboratory conditions. The experimental preparation group consisted of several healthy adult men. Normal adults who keep their eyes closed when they are awake will produce clearer alpha waves of about 10 Hz, which disappear when they open their eyes. By observing the alpha wave, we can analyze the quality of the signal collected by the system。

After the collected data is analyzed by Matlab in Figure 5.13, it can be seen that the phenomenon of opening and closing the eyes is obvious, and a waveform of about 10Hz is very clear in the time domain and frequency domain, indicating that the quality of the signal collected by the system is good.

Clinical test:

In addition to experiments on normal people, this article also does related clinical experiments. In the Huashan Hospital affiliated to Fudan University, this system has passed the safety certification of the Quality and Safety Administration, and has got the permission of the Huashan Hospital to conduct clinical trials. Figure 5.14 is the scene where the clinical trials in the hospital. The collected data is shown in Figure 5..

Figure 5.12 System verification in lab environment

Figure 5.13 Analysis of α-wave during the testing phase

Since the patient is in a coma, there is no manifestation of the disease during the EEG signal acquisition period, and the patient's condition tends to be stable. From the perspective of the signal amplitude, the signal amplitude is within the normal range. In order to further verify the EEG of the EEG collected by the system, this article also uses the existing EEG acquisition equipment (Nicolet) in the hospital to collect the EEG of the patient at the same time. In order to ensure the validity of the experiment, in the course of the experiment, after the multi-modal brain monitoring system collects the data, the Nicholas acquisition system is immediately installed for the patient. As the patient's condition tends to be stable and there is no change, we can think of the two signals collected by the system should be roughly the same.

Figure 5.14 Illustration of the system in action collecting clinical data

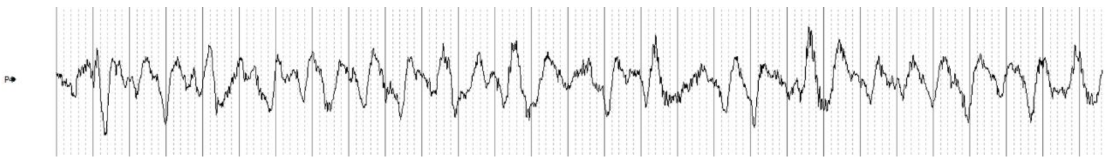


Figure 5.15 EEG waveform at F3 position collected by Nicolet

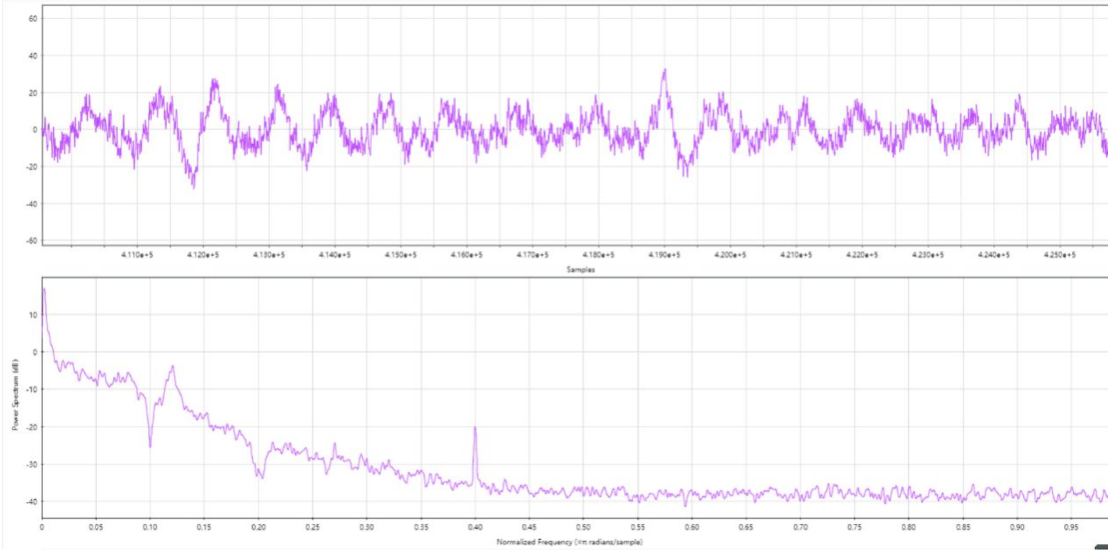


Figure 5.16 EEG waveform at F3 position collected by this system

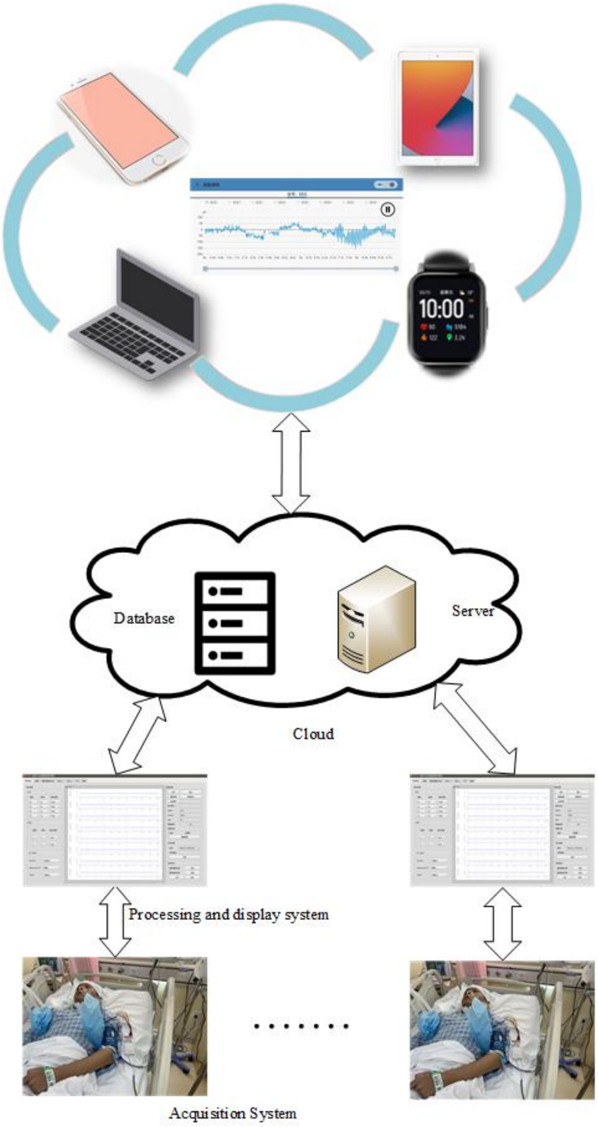


Figure 5.15 multi-modal brain monitoring system

So far, a complete set of the multi-modal brain monitoring system has been built successfully, and the structure of the system is shown in Figure 5.15. In NICU, this system can be installed at the bedside of all patients. Each device monitors the patient's EEG, NIRS, ICP and other signals in real-time, and displays and analyzes the data on the bedside data analysis and display platform. Furthermore, the data is sent to the Cloud database for storage. On the other hand, the backend is built on the cloud server to provide services for mobile applets. The multi-modal brain monitoring system built in this article will provide convenience for medical workers. Medical workers can use mobile devices such as mobile phones to monitor the status of patients in real-time remotely. With the help of AI algorithms such as deep learning, the system can also assist doctors in analyzing patients, thereby making the entire treatment process more intelligent.

5.4 Chapter summary

This chapter covered the last details of the development of the proposed IoT neural monitoring system. Considering that the multi-modal brain monitoring system needs to collect a large number of physiological signals, each physiological parameter usually has a different data format. That makes it difficult to use the same format for all physiological parameters to store data, and data management is also more complicated. Therefore, this thesis builds a MongoDB database based on a cloud server. This database has no strict requirements on the data format and is very suitable for this complex application scenario. As well as the back-end applications for WeChat applets, Django is an open-source, robust, and widely used web framework. Based on Django, it is easy to build web back-end applications. This article combines the actual situation on a cloud server. Develop the back end of the system, combined with the database, to provide reliable services for the entire Internet of Things system. The system has been tested in a laboratory environment and a clinical environment and achieved the expected results. Furthermore, it can continue to add more powerful functions on this basis in the future.

6 Conclusions

6.1 Summary

Neuro-intensive care usually responds to some critically ill patients with serious illness. For complex and changeable diseases, it is essential to understand the patient's physiological parameters in time for the treatment of patients. However, the patient's complex condition and some complications will seriously affect the doctor's efficiency in diagnosing the patient's condition. The development of a multi-modal brain monitoring system that includes multiple physiological parameter monitoring will help change this situation. Furthermore, the benefits of an IoT system based on AI algorithms such as deep learning are evident in this field. Such a system can effectively help doctors diagnose the condition, reduce the rate of misjudgment, and improve efficiency.

Although some scholars have done some related research in the past, there are few related applications in clinical practice, and most medical monitoring equipment can only monitor one physiological parameter. Disease diagnosis based on artificial intelligence algorithms has not been put into clinical applications. Thus, this thesis mainly studies about it, and the main research results are as follows:

Firstly, based on the artificial intelligence algorithm of deep learning, to assess the consciousness level of patients with consciousness disorders, combined with the clinical data provided by Huashan Hospital, a conclusion can be drawn: EEG signals are correlated with the patient's consciousness level. Based on clinical data, the judgment accuracy rate of UWS and MCS reached 85%. In terms of epilepsy monitoring, the recognition rate of epilepsy monitoring based on the CNN network in clinical data has reached about 95%, which has high application value.

Secondly: This thesis combines artificial intelligence algorithms to build an Internet of Things system. First of all, a GUI interface is designed at the bedside to facilitate medical staff to observe and analyze the collected physiological signals. Then, build a MongoDB database with cloud server to store the collected EEG data. Finally, the back end of the WeChat applet is built on the cloud server to process the data and communicate with the WeChat applet.

Thirdly, in order to verify the effectiveness of the system, we use this system to conduct clinical experiments and verify its reliability from hardware systems to software algorithms. The EEG signal collected by the system has good quality, strong anti-interference ability and high signal-to-noise ratio. The IoT system built is more comprehensive and has good stability.

6.2 Future work

This thesis covers an in-depth analysis of AI algorithms in assessing the consciousness level of patients with consciousness disorders, and the design, development and implementation of a multi-modal IoT monitoring system based on the most appropriate Edge-AI algorithms. A complete system is validated and tested. However, it is evident that the work can be improved in multiple directions. In the future, research and expansion of the current results can be continued in the following areas.

Firstly, deep learning algorithms are greedy for data. The data sets used in this thesis are not too much. In addition, this thesis does not make more improvements to the algorithm, especially in assessing the level of consciousness of patients. Considering that there is a very high error rate in clinical assessment of the level of consciousness, this may become one of the hot directions in the future. Secondly, diagnose diseases based on physiological parameters, which has higher requirements for data quality. However, clinical data collection is subject to many interference factors, and how to eliminate these interferences is also one of the main points to be considered. Thirdly, the disease of the critically ill patient is very complicated and accompanied by various complications. In this case, the collected physiological signals will also be greatly affected. For example, in some patients with skull flaps removed, the EEG amplitude collected in this area will be significantly larger than other areas. Finally, there is still a lot of room for improvement in many functions of the IoT system built, and the functions of the system can be improved from the perspective of users.

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