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Application of Deep Learning in the Classification of EEG Signals of Parkinson's Disease Patients

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Abstract. This article summarizes research on classifying electroencephalogram (EEG) signals of Parkinson's disease (PD) patients using deep learning technologies. Parkinson's disease is a common neurodegenerative disorder that severely affects quality of life. EEG signals provide valuable information about brain activity. Therefore, analyzing and classifying the EEG signals of PD patients can aid in early diagnosis and treatment. The paper outlines the assessment metrics and cross-validation methods in the diagnosis of Parkinson's disease, highlighting the effectiveness of deep learning in diagnosis. The key technologies reviewed in the article include Wavelet Packet Transform (WPT) and Deep Residual Neural Networks (DRSN), with the WPT-DRSN method achieving up to 99.92% prediction accuracy in the binary classification task of PD patients. Furthermore, this method has also been applied to more complex classweweification tasks, such as categorizing PD patients, REM sleep behavior disorder patients, and healthy controls, maintaining high accuracy. When analyzing Parkinson's disease EEG with the CRNN model, the accuracy is high, but the sample size is small and the model interpretability is limited, necessitating further validation and improvement. For EEG-based PD diagnosis and classification methods, high accuracy was achieved through ICA preprocessing, CSP feature extraction, and ensemble learning classifiers. Future research should consider the integration of multimodal data fusion, deep learning, and NLP technologies, as well as the development of personalized models to enhance the accuracy of PD diagnosis.

Keywords: Deep Learning; Publishing; Parkinson's Disease; EEG Signals; Classification.

1. Introduction

Parkinson's disease is a common neurodegenerative disease, with symptoms including muscle stiffness, tremors, and movement disorders. With the aging population, the incidence of Parkinson's disease is gradually increasing, bringing a heavy burden to patients and their families. Early diagnosis and intervention are crucial for delaying disease progression and improving patients' quality of life. Brain electrical signals, as an important biological signal, can provide valuable information about brain activity. EEG is the electrophysiological recording of brain neuron activity, which can reflect features such as synchronicity and frequency oscillations of brain neurons. In patients with Parkinson's disease, EEG often shows abnormal synchronous oscillations at specific frequencies, such as excessive beta wave activity. This abnormal signal can be utilized for early diagnosis and monitoring of Parkinson's disease. Therefore, analyzing the brain EEG of Parkinson's disease patients contributes to early diagnosis and treatment.

Deep learning is widely used in the classification of Parkinson's disease EEG signals. By processing EEG signal data with deep neural network models, higher-level features can be extracted, leading to more accurate classification and diagnosis of Parkinson's disease. Deep learning techniques such as Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) are employed for feature extraction and pattern recognition of EEG signals to achieve efficient Parkinson's disease classification. In recent years, deep learning, as a popular technology in the field of artificial intelligence, has made significant achievements in areas such as image recognition and speech recognition. The strong feature extraction and learning capabilities of deep learning models make them effective tools for handling complex data and solving classification problems. With the rapid development of deep learning technology, more and more research is beginning to apply it to the field of biomedicine, including the analysis of brain electrical signals.

This article aims to explore the characteristics of brain electrical signals in Parkinson's disease patients and propose a classification method based on deep learning. By collecting and analyzing brain electrical signal data from both groups, the research team hopes to accurately distinguish Parkinson's disease patients from healthy individuals, providing important references for the early diagnosis and treatment of Parkinson's disease. Additionally, this article aims to explore the potential application of deep learning technology in the classification of Parkinson's disease brain electrical signals, providing new ideas and methods for research in related fields.

In the following sections, this paper will first introduce Parkinson's disease and its relationship with brain electrical signal characteristics, then delve into the application of deep learning in the analysis of brain electrical signals, and finally present experimental results and conduct in-depth analysis. Through the conduct of this study, this paper hope to provide a more objective and accurate method for the early diagnosis and treatment of Parkinson's disease, bringing new insights and breakthroughs to research and clinical practice in related fields.

2. Parkinson's disease and brain electrical signal characteristics

2.1. Overview of Parkinson's Disease

Parkinson's disease is a common neurodegenerative disease, with main symptoms including muscle stiffness, tremors, and movement disorders. These symptoms are caused by dysfunction in motor control due to a decrease in dopamine levels in the brain. Parkinson's disease usually occurs in middle-aged and elderly individuals, but there are also a few cases found in younger people, known as early-onset Parkinson's disease.

The exact cause of Parkinson's disease is currently unclear, but it is believed to be related to genetic factors, environmental factors, and neurodegeneration. Most cases of Parkinson's disease are sporadic, meaning there is no clear family history of the disease. However, some cases are caused by genetic mutations, leading to hereditary Parkinson's disease. Environmental factors such as pesticides, heavy metal poisoning, are also considered to be associated with the occurrence of Parkinson's disease.

Diagnosis of Parkinson's disease typically relies on the patient's symptoms and neurological examination. In addition, imaging tests such as magnetic resonance imaging (MRI) and positron emission tomography (PET) can also be used for diagnostic assistance. Currently, the commonly used diagnostic criteria for Parkinson's disease are based on the Unified Parkinson's Disease Rating Scale (UPDRS) developed by the British Parkinson's Disease Association to assess the severity of symptoms in patients.

Treatment methods for Parkinson's disease mainly include drug therapy, surgical treatment, and rehabilitation therapy. The primary goal of drug therapy is to alleviate symptoms by supplementing dopamine. Surgical treatments such as deep brain stimulation (DBS) may be considered when drug therapy is ineffective. Rehabilitation therapy includes physical therapy, speech therapy, etc., aiming to help patients regain daily living abilities.

In summary, Parkinson's disease is a chronic disease that requires long-term treatment and management. Early diagnosis and treatment of Parkinson's disease are crucial and can effectively delay disease progression, improving patients' quality of life. Brain electrical signals, as an important biological signal, are of significant importance in the research and diagnosis of Parkinson's disease. In the following sections, this paper will focus on the brain electrical signal characteristics of Parkinson's disease patients and explore how to use deep learning techniques to classify and analyze these features, with the aim of enhancing early diagnosis of Parkinson's disease.

2.2. The Importance of EEG Signals in Parkinson's Disease

Parkinson's disease, as a common neurodegenerative disorder, severely impacts the quality of life of patients. Early diagnosis and treatment are crucial in clinical practice to slow down the progression of the disease. Brain electrical signals, as an important biological signal, record the activity of brain neurons and contain rich information. For patients with Parkinson's disease, brain electrical signals can reflect the characteristics of their brain activity, helping to reveal patterns in the development of the disease. Therefore, in-depth research on the brain electrical signals of Parkinson's disease patients contributes to a better understanding of the disease's pathogenesis and provides a scientific basis for clinical diagnosis and treatment.

In Parkinson's disease research, brain electrical signals play a unique and significant role. By analyzing the brain electrical signals of patients, changes in signals in different frequency bands can be detected, leading to the inference of abnormal patterns in brain activity. These abnormal patterns may be related to the unique neuronal damage and synaptic dysfunction in Parkinson's disease. Through detailed studies of the temporal features, spectral features, and coherence features of brain electrical signals, the changing patterns of brain activity in Parkinson's disease patients can be revealed, providing important clues for the diagnosis and treatment of the disease.

Brain electrical signals can also serve as a non-invasive biological signal, facilitating the early diagnosis of Parkinson's disease. Compared to traditional imaging examinations, brain electrical signal acquisition is simple, cost-effective, and can be repeated multiple times. By comparing and analyzing the brain electrical signals of Parkinson's disease patients and healthy control groups, differences between the two can be identified, enabling early screening for Parkinson's disease. This is of great significance for early intervention and treatment to delay disease progression.

In disease management and treatment, the application of brain electrical signals is also of great importance. Monitoring changes in patients' brain electrical signals can provide real-time reflections of disease progression, offering objective evidence for doctors to adjust treatment plans. Furthermore, deep learning algorithms based on brain electrical signals can achieve individualized diagnosis and treatment for patients, providing clinicians with precise diagnostic tools. This personalized treatment approach helps improve treatment outcomes, reduce unnecessary drug side effects, and enhance the quality of life for patients.

Brain electrical signals hold an irreplaceable position in the research and clinical application of Parkinson's disease. By delving into the information contained in brain electrical signals, a better understanding of the pathogenesis of Parkinson's disease can be achieved, providing a scientific basis for the early diagnosis and treatment of the disease. Additionally, monitoring and analyzing brain electrical signals offer new avenues for formulating personalized treatment plans, potentially bringing better medical experiences and treatment outcomes for Parkinson's disease patients.

3. The Application of Deep Learning in EEG Signal Analysis

3.1. Overview of Deep Learning Algorithms

Deep learning is a machine learning algorithm based on artificial neural networks, and its core idea is to learn high-level abstract representations of data through a multi-level neural network structure. In the analysis of electroencephalogram signals, the application of deep learning algorithms is gradually receiving widespread attention and use.

3.1.1. Neural network structure

In deep learning algorithms, neural networks are an essential component. A neural network consists of multiple neurons, with each neuron receiving inputs from the neurons in the previous layer and calculating outputs through an activation function. By connecting multiple layers of neurons and transmitting information, neural networks can learn complex feature representations of input data. In the task of classifying electroencephalogram signals, neural networks can effectively learn feature representations of these signals, enabling differentiation between signals of different categories.

3.1.2. Identification of Parkinson's disease based on clinical data investigation using deep learning technology

The article first summarizes multiple datasets used for PD diagnosis and categorizes them based on their frequency of use in the literature. This provides researchers with a clear indication of which datasets are the most important and commonly used in the field. It then introduces various evaluation metrics for assessing model performance on these datasets, such as accuracy, recall, F1 score, etc. These metrics are crucial for comparing results across different studies.

The article also discusses various cross-validation (CV) techniques, which is an important aspect to ensure the reliability of evaluation results. Based on the same data set and performance evaluation parameters, the literature evaluates the experimental results of various PD diagnostic methods.(Usage and percentage of different DL models in PD diagnostic methods, as shown in Figure 1) Through this contribution, researchers can easily identify proposed models that perform well.

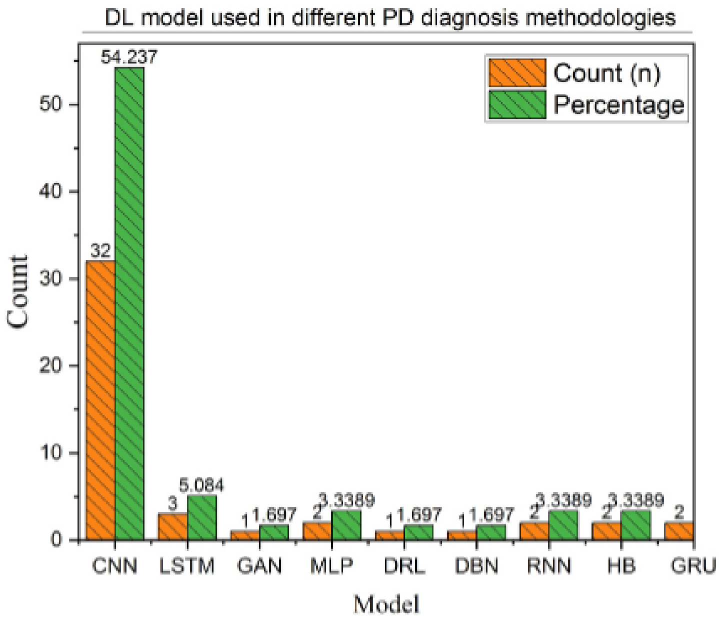

Figure 1. The number and percentage of DL models used in the proposed Parkinson's disease diagnostic method

The proportion of CNN models used in the study is 54.237% (n = 32). Similarly, LSTM models account for 5.084% in the study (n = 3). Other models include GAN (n = 1, 1.697%), MLP (n = 2, 3.3389%), DRL (n = 1, 1.697%), DBN (n = 1, 1.697%), RNN (n = 2, 3.3389%), HB (n = 2, 3.3389%), and GRU (n = 2, 3.3389%).

The literature mentions that due to its ability to automatically extract distinctive features from biological markers (such as imaging and acoustic markers), deep learning methods have become one of the most effective algorithms in the diagnosis of Parkinson's disease. This contribution enables the research community to more easily select the most important datasets, performance evaluation metrics, and cross-validation techniques based on the popularity of the dataset and the field application [1].

3.1.3. Time-Frequency Analysis Combined with Deep Learning for EEG Analysis of Parkinson's Disease

The study of scroll volumes integrates two time-frequency analysis methods: the Tunable Q-factor Wavelet Transform (TQWT) and the Wavelet Packet Transform (WPT). These methods are combined with a Deep Residual Shrinkage Network (DRSN). By analyzing clinical sleep EEG data from Shaanxi Provincial People's Hospital, the study classifies Parkinson's Disease (PD) and related sleep behavior disorders.

The study found that in binary classification tasks, the WPT-DRSN method achieved a prediction accuracy of up to 99.92% for PD. In the three-class (including PD, REM sleep behavior disorder, and normal control group) and four-class (adding PD with REM sleep behavior disorder combination) tasks, the accuracy of WPT-DRSN reached 97.81% and 92.59%, respectively, surpassing the TQWT-DRSN method's 95.20% and 90.46%.

This study is the first to use TQWT and WPT as preprocessing steps to extract richer and more distinctive time-frequency features. These features are then used to train DRSN, which fully leverages the strengths of both methods, enhancing the expressive power of the features. DRSN optimizes the feature representation of signals through its deep residual learning framework, reducing information loss during model training, which is particularly crucial for highly complex data like EEG signals. The study not only improves the accuracy of PD diagnosis and monitoring but also provides new research directions and practical foundations for the application of deep learning in medical imaging and signal processing. In particular, in the diagnosis and prediction of RBD in PD patients, it demonstrates the strong capability of deep learning feature extraction and classification. While this study has made significant progress in PD monitoring and diagnosis, the research team also points out the shortcomings of current methods in dealing with specific sleep disorders, such as REM sleep behavior disorders, providing directions for further research [2].

3.1.4. Convolutional-recurrent neural network method for classifying resting-state electroencephalogram in Parkinson's disease

The main focus of this article is to improve the accuracy and efficiency of diagnosing, prognosing, monitoring, and planning treatment strategies for Parkinson's disease (PD) through quantitative analysis of electroencephalogram (EEG) data. This study aims to provide a more effective tool for the diagnosis and monitoring of Parkinson's disease by classifying resting-state EEG data of PD patients and healthy controls (HC) using a convolutional recurrent neural network (CRNN model).

The author of the article proposed and validated the potential value of EEG quantitative analysis in PD research: through multiple case studies, this article emphasizes the importance of quantitative EEG in identifying abnormal brain electrical activity features in PD patients. These features include but are not limited to changes in spectral characteristics based on wavelet packet decomposition coefficients, changes in entropy, and enhanced coherence between frontal lobes, especially in the frequency range of 10-35 Hz.

The author proposed a lightweight deep learning model for classifying PD and HC individuals' resting-state EEG, which consists of a Recurrent Neural Network (RNN) composed of Convolutional Neural Networks (CNNs) and Gated Recurrent Units (GRUs). The CRNN model extracts spatiotemporal features between EEG channels through a 1D CNN layer and discovers time-related features relevant to classification using GRUs, achieving a classification accuracy of 99.2%. Compared to traditional machine learning models based on manual features, the CRNN model automatically learns features, reducing additional data processing steps.

The CRNN model achieved high accuracy of 99.2% in classifying PD and HC, with precision of 98.9% and recall of 99.4%. Furthermore, the research team investigates whether the prediction accuracy of the CRNN model is mainly affected by phase information or spectral power information, as shown in Figure 2. The team's analysis also revealed that the model is particularly sensitive to phase information of signals like dopamine drugs and EEG signals.

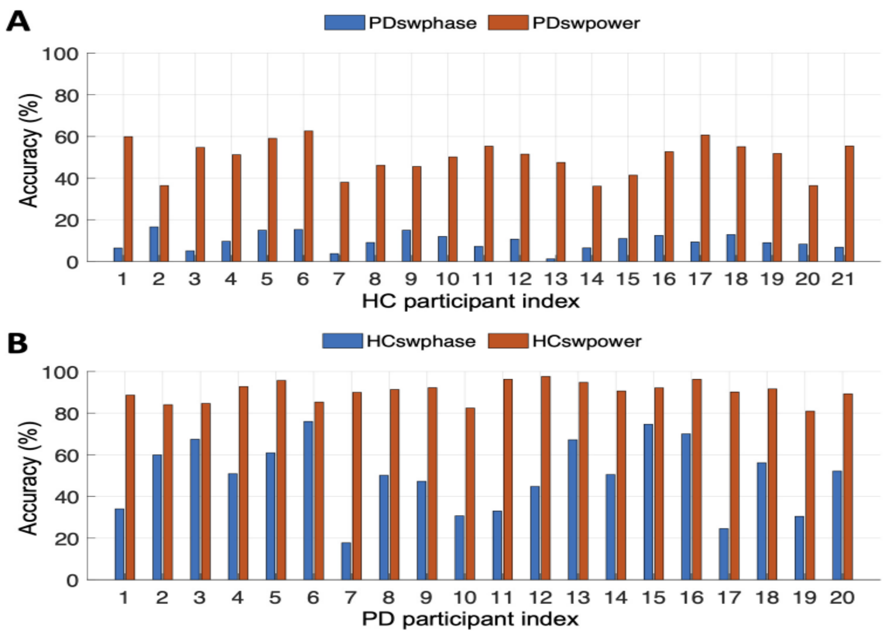

Figure 2. The accuracy of the CRNN model on EEG datasets with phase or power exchange. The x-axis represents participant indices. (A) Phase or spectral power is replicated from healthy participants to Parkinson's disease EEG samples. (B) Phase or spectral power is replicated from Parkinson's disease participants to healthy control EEG samples.

The horizontal axis represents participant indices from whom phase or spectral power is copied. (A) Phase or spectral power copied from healthy participants to Parkinson's disease EEG samples. (B) Phase or spectral power copied from Parkinson's disease participants to healthy control EEG samples.

The study demonstrates the potential and advantages of using deep learning methods in the diagnosis of neurological diseases by analyzing EEG in the resting state with the CRNN model. In addition to high accuracy in classification performance, the study also reveals the model's sensitivity to the phase information of EEG signals, providing a new perspective and approach for early diagnosis and detection of neurodegenerative diseases such as Parkinson's disease in the future.

The author also summarized the unresolved issues. Such as the sample size problem: the small sample size is a significant limitation of this study. It is relatively difficult to find public EEG data from healthy individuals matching the age of PD. Limitations of model interpretability: despite attempts to test the model through simulation studies, the interpretability of the proposed model still has limitations.

In future development, research fields are actively exploring more advanced models such as attention-based LSTM to improve the prediction process and interpretability of time series forecasting. Future research needs further improvement and validation of the models' performance in clinical practice, especially considering the generalization ability and sample size impact of the models. Currently available PD EEG data is scarce, developing a collaborative platform to share data is crucial for validating the generalization ability of the proposed models [3].

3.1.5. Diagnosing and classifying Parkinson's disease using ensemble learning and 1D-PDCovNN

The core academic contribution of this article mainly lies in the development of Parkinson's disease (PD) diagnosis and classification methods based on electroencephalogram (EEG) signals. Specifically, the team proposed a novel PD diagnosis and classification framework utilizing ensemble learning and 1D convolutional neural network (1D-PDCovNN) technology. Figure 3 are shown the PD diagnosis and classification system block diagram. The team's research method can be roughly divided into three steps: (1) Preprocessing: Removing blink noise from EEG signals using

Independent Component Analysis (ICA). (2) Feature extraction: Extracting features from EEG signals using Common Spatial Patterns (CSP) method. (3) Classification: In the third stage, utilizing Dynamic Classifier Selection (DCS) within Modified Local Accuracy (MLA) ensemble learning method composed of seven different classifiers.

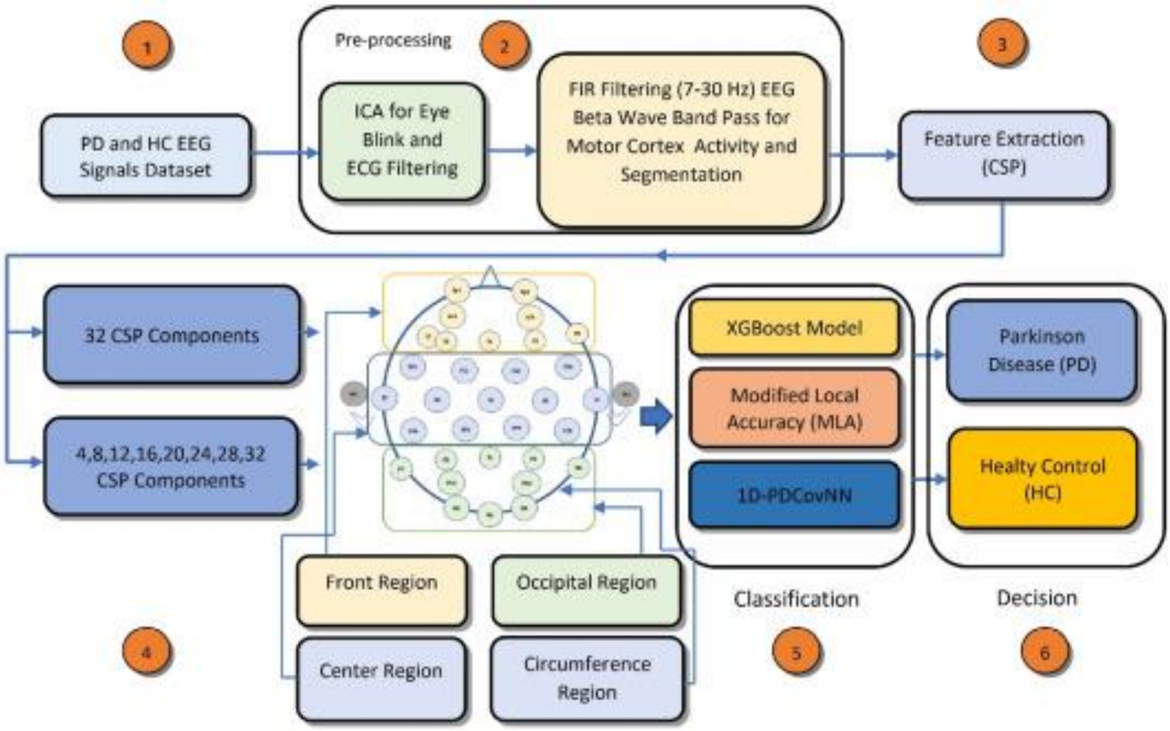

Figure 3. PD Diagnostic Classification System Diagram.

The team utilizes the DCS and MLA methods primarily because this combination can effectively enhance diagnostic accuracy. Specifically, DCS can select the most suitable classifier for the current data sample from multiple classifiers, while the MLA method selects by considering the accuracy of classifiers on local data sets, which helps improve overall diagnostic performance. According to the research, this method achieved an accuracy of 99.31%, significantly higher than single classifiers or other non-ensemble methods.

The main findings of the study are as follows:

Accuracy: DCS achieved a combined accuracy of 99.31% in MLA, indicating significant effectiveness in diagnosing and classifying PD through EEG signals.

Performance Comparison: The study also compared the efficiency of XGBoost, 1D-PDCovNN, and DCS in MLA, as well as the classification effects of other algorithms on PD and Healthy Control (HC) EEG signals. The results show that these three models outperform others in 32 EEG signal channels from four scalp regions, with the XGBoost model performing the best in all four regions.

Band Influence: The study further explored the impact of motor cortical activity displayed in the 7-30 Hz frequency band on PD diagnosis and classification, providing additional validation for the proposed method's effectiveness.

This study successfully developed a PD diagnosis and classification method based on EEG signals (Figure 4 shows the block diagram of the 1D-PDCovNN model in the team's proposed new PD diagnosis and classification framework), achieving high accuracy in early PD diagnosis through the integration of ICA preprocessing, CSP feature extraction, and ensemble learning classifiers. This method not only enhances the accuracy and efficiency of PD diagnosis but also offers new insights for future PD research and treatment. However, the study also identified potential limitations, including the possibility of inaccurate PD diagnosis when patient medical history, symptoms, and physical examinations are not considered. These findings provide an important foundation and direction for further research.

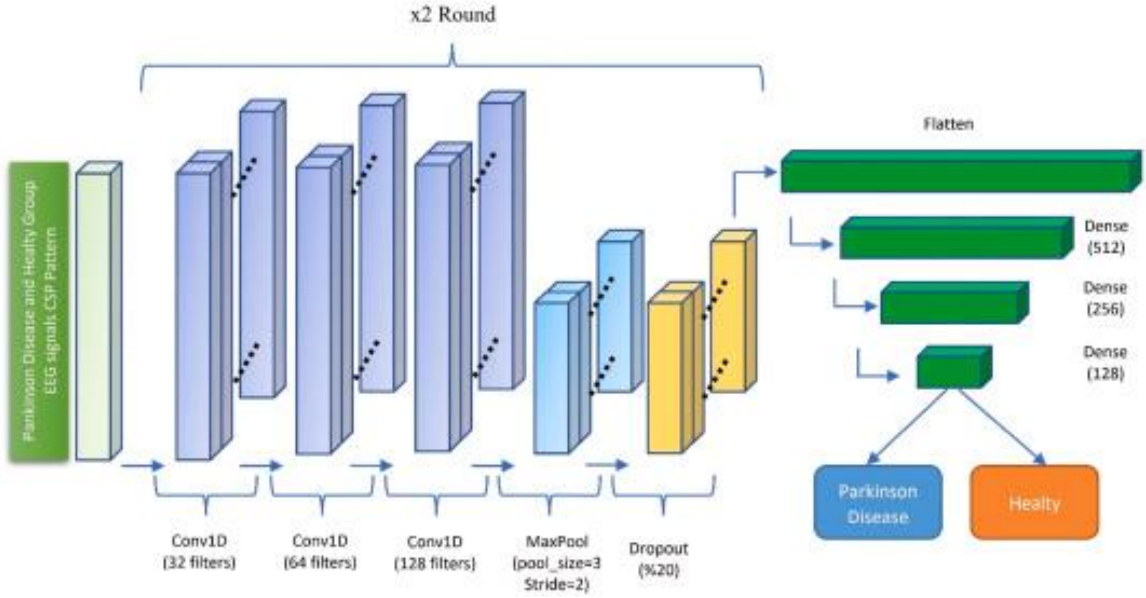

Figure 4. 1D-PDCovNN model block diagram.

In the future development, the author believes that overcoming these limitations can be approached from three aspects.

Multimodal data fusion: Future research should consider integrating various types of data, such as medical history, symptom descriptions, physical examination results, and other biomarkers, along with EEG signals as input data. This multimodal data fusion can provide more comprehensive disease information, thereby improving the accuracy and reliability of PD diagnosis.

Deep learning and Natural Language Processing (NLP) techniques: Deep learning models can be used to process and integrate different types of data. For example, NLP techniques can be utilized to analyze patients' medical histories and symptom descriptions, transforming this information into a format that can be processed by machine learning models.

Personalized model development: By constructing personalized diagnostic models optimized based on individual patient-specific information (including genetic information, lifestyle habits, medical history, etc.), the accuracy of diagnosis can be further enhanced. This necessitates future research to gather and analyze data across more dimensions [4].

3.1.6. Using transferable deep learning for Parkinson's disease EEG classification

This study aims to assist in the diagnosis of Parkinson's disease (PD) and other neurological disorders by analyzing electroencephalogram (EEG) signals. The research utilizes an existing anonymous public EEG dataset and employs a deep learning architecture for analysis, aiming to explore the application of EEG in diagnosing complex neurological diseases. The study has developed a CNN model specifically designed for EEG signals, which can automatically extract and learn meaningful features for PD diagnosis from EEG signals. Compared to traditional machine learning methods, this approach eliminates the need for manual feature extraction, greatly simplifying the preprocessing steps.

CNN is capable of automatically learning complex and high-level features from raw EEG signals, which is crucial for understanding the intricate physiological processes of neurological diseases like PD. By using leave-one-out cross-validation, the research achieved an accuracy of 80.4% among Parkinson's patients (epoch-level accuracy of 72.7%) and maintained an accuracy of 82.8% (epoch-level accuracy of 75.7%) when tested on an independent external dataset, demonstrating the effectiveness of CNN in diagnosing PD. The CNN model showed consistent performance across different datasets, indicating its good generalization ability, which is essential for handling EEG data from various sources and patients in practical applications.

Through EEG signal analysis, the study found that quantitative electroencephalogram (QEEG) indices can effectively differentiate Parkinson's patients from healthy control groups. This discovery provides strong evidence for the early diagnosis and monitoring of Parkinson's disease and other neurological disorders using EEG technology.

The research provides open-source code, laying the foundation for future studies to explore different deep learning architectures, investigate other neurological disorders, and involve larger datasets. This contributes to accelerating the adoption of objective computational methods for diagnosing and monitoring neurological diseases [5].

3.2. Advantages of Deep Learning in EEG Signal Classification

Deep learning, as a powerful machine learning technique, has the capability to efficiently learn features and classify on complex datasets, gradually becoming a research hotspot in the field of analyzing EEG signals. In the task of classifying EEG signals of Parkinson's disease patients, deep learning has demonstrated many advantages, making it an effective analytical method.

Deep learning possesses strong feature learning capabilities. EEG signal data typically exhibit high dimensionality and complexity, where traditional feature extraction methods often require manually designed feature extractors and struggle to fully exploit the latent information in the data. Deep learning models, through multi-layer neural network structures, can automatically learn abstract feature representations from the data, thereby better capturing relevant information in EEG signals, improving classification accuracy and generalization capability.

Deep learning showcases strong data fitting abilities. Between Parkinson's disease patients and healthy control groups, significant differences may exist in EEG signal data, adding complexity to the classification task. Traditional machine learning algorithms handling high-dimensional, non-linear data often require extensive feature engineering and hyperparameter tuning, and are prone to getting stuck in local optimal solutions. Deep learning models, with their multi-layer non-linear structures, can better fit the complex data distribution, enhancing the robustness and generalization capability of classification.

Deep learning also exhibits good scalability and universality. Different deep learning models can be designed for classifying various types of EEG signal datasets, adjusting network structures and hyperparameters to adapt to different data features and task requirements. Moreover, successful experiences of deep learning techniques in other domains can be leveraged to enhance model design and optimization efficiency for EEG signal classification tasks.

Deep learning further offers strong interpretability. By visualizing intermediate layer feature maps of neural networks, one can intuitively understand the model's understanding and judgment basis on EEG signal data, further enhancing the model's credibility and interpretability. This is crucial for the widespread clinical application of deep learning models, providing doctors and researchers with more intuitive and reliable diagnostic information.

Deep learning presents numerous advantages in classifying EEG signals of Parkinson's disease patients, including robust feature learning capabilities, data fitting abilities, scalability and universality, as well as good interpretability. These strengths position deep learning technology with broad application prospects in the field of EEG signal analysis, offering crucial support and assistance for early diagnosis and treatment of Parkinson's disease. The continuous development and application of deep learning will further drive innovation and progress in EEG signal analysis technology, bringing more opportunities and challenges to the fields of neuroscience and clinical medicine.

4. Conclusion

Through the analysis and discussion of the above research results, this paper found that methods based on deep learning perform well in the classification of brain electrical signals of Parkinson's disease patients. The models discussed in the article improved accuracy and also showed good stability and generalization. This indicates that the application of deep learning technology in the biomedical field has broad development prospects, providing important support for the early diagnosis and treatment of Parkinson's disease.

By analyzing the above research results, I have summarized the effectiveness and feasibility of methods based on deep learning in the classification of brain electrical signals of Parkinson's disease patients, providing new ideas and methods for related research fields. The application of deep learning technology in the biomedical field can guide future research and clinical practices.

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