

Research on the Recognition of Mild Cognitive Impairment Based on Deep Learning

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ABSTRACT With the accelerating process of global population aging, the importance of early diagnosis and intervention for mild cognitive impairment (MCI), as a prodromal stage of dementia, has become increasingly prominent. Accurate early identification of MCI is the key to delaying disease progression and reducing the incidence of senile dementia. Traditional recognition methods mostly rely on scale assessment and clinical experience of doctors, which have problems such as strong subjectivity, low efficiency, and insufficient standardization. Deep learning technology has powerful capabilities in automatic feature extraction and pattern recognition, and can mine hidden features in medical images, physiological signals, and behavioral data. This paper takes deep learning algorithms as the core to carry out research on automatic recognition of MCI. It sorts out the pathogenesis characteristics and existing recognition methods of MCI, constructs recognition models based on convolutional neural networks and recurrent neural networks, and uses public medical datasets to complete model training and verification. A series of comparative experiments are designed, and four evaluation indicators are used to test the recognition accuracy and stability of the models. The results show that deep learning models can effectively extract features related to cognitive impairment, and their recognition accuracy for MCI is better than traditional manual assessment and machine learning methods. This study can provide technical reference for non-invasive clinical screening and intelligent auxiliary diagnosis, as well as theoretical support for the construction of an early warning system for geriatric neurological diseases. The EEG preprocessing and temporal modeling connect the recognition framework with biomedical bioelectrical signal analysis.

INDEX TERMS mild cognitive impairment, deep learning, eeg signal, medical imaging, bioelectrical signal processing

I. INTRODUCTION

A. RESEARCH BACKGROUND

IN 2011, the guidelines of the National Institute on Aging and the Alzheimer's Association defined AD in three stages: preclinical AD (early pathological changes in the brain of cognitively normal individuals), mild cognitive impairment (MCI) as the symptomatic stage before dementia, and dementia stage [1,2]. At present, MCI is generally defined as a mental syndrome characterized by cognitive decline beyond that expected for an individual's age and educational background [3]. It manifests as more severe cognitive decline than normal aging, but the symptoms are not severe enough to meet the diagnostic criteria for dementia. MCI is regarded as a transitional stage between typical aging and dementia, and often eventually develops into AD [4]. Timely identification of MCI is a critical window, which facilitates the implementation of early interventions such as cognitive training, lifestyle adjustment, and potential drug therapy. These interventions may have significant effects on

delaying the progression of AD. Therefore, early diagnosis of MCI has extensive clinical, social, and economic benefits [5].

In recent years, electroencephalogram (EEG) has attracted extensive attention due to its great potential in the diagnosis of AD and other dementias [6], which has inspired many researchers to study the diagnosis of MCI patients by analyzing EEG with machine learning technology [7]. However, the EEG of MCI patients does not have obvious features like that of epilepsy patients, which requires traditional machine learning algorithms to manually extract features based on prior knowledge. In contrast, deep learning can overcome some limitations of traditional machine learning techniques due to its ability to automatically learn features from data without relying on expert prior knowledge for feature selection. The rapid development of deep learning and its advantage of no manual feature extraction make it a high-profile field in the advancement of MCI diagnostic technology [8].

B. RESEARCH SIGNIFICANCE

Current domestic research on MCI mostly focuses on clinical medicine and nursing. Existing relevant studies mainly analyze the predisposing factors of the disease and explore corresponding intervention and nursing plans. There is still much room for improvement and expansion in domestic research on intelligent recognition of MCI based on artificial intelligence. This paper will build a deep learning recognition framework adapted to the data characteristics of MCI and improve the application system of deep learning in the field of geriatric cognitive disease recognition. This study can provide theoretical reference for the subsequent intelligent recognition of similar neurological diseases and practical model application reference.

C. RESEARCH STATUS AT HOME AND ABROAD

In the field of EEG feature extraction, it can be mainly divided into four parts: time domain [9], frequency domain [4], time-frequency domain [10], and spatial domain [11]. Hogan *et al.* [12] found that the EEG entropy of MCI patients is usually low through entropy analysis when studying the differences between MCI and healthy elderly people. Al-Qazzaz *et al.* [13] analyzed the EEG characteristic differences between MCI patients and normal people using sample entropy respectively, and found that the EEG complexity of MCI patients decreased, thus verifying that sample entropy can be used as a biomarker to measure cognitive function. McBride *et al.* [14] found that multiscale entropy of EEG in AD, MCI, and healthy elderly people is closely related to memory impairment by comparison. Maturana-Candelas *et al.* [15] used multiscale sample entropy and refined multiscale spectral entropy to evaluate the complexity of EEG. The results revealed that these two entropies can reflect neurological disorders related to dementia development, which may help to discover new biomarkers to track the evolution of AD.

Traditional machine learning algorithms require a lot of prior knowledge as the basis, while deep learning algorithms can avoid the problems of preprocessing and feature extraction caused by machine learning algorithms, and can obtain higher classification accuracy than machine learning algorithms. In recent years, although many researchers still use traditional machine learning algorithms to classify EEG, with the rapid development of deep learning, a considerable number of researchers have begun to explore the application of deep learning in EEG classification tasks [16]. The success of deep learning largely relies on a large amount of training data to avoid insufficient model generalization ability. Due to individual differences in EEG data, difficulties in clinical data collection, and preprocessing steps, the amount of available EEG data is further reduced, resulting in EEG data being small-sample datasets in many cases. Small-sample datasets are more prone to overfitting in deep learning training. Therefore, data augmentation methods are proposed to solve the problems brought by small-sample data to deep learning.

Data augmentation can effectively improve the generalization ability of deep learning and reduce the cost of collecting labeled data [17]. Zhang *et al.* [18] converted motor imagery EEG data into spectrograms using short-time Fourier transform, then used deep convolutional generative adversarial networks to augment the dataset, and designed a specific program to retain only excellent generated data before classification with CNN. Finally, the highest average classification accuracy of 83.2% and 93.2% was obtained on BCI Competition IV datasets 1 and 2b respectively. Schwabedal *et al.* [19] used Fourier transform algorithm to generate surrogate data of EEG, EOG, and EMG in the CAPSLPDB sleep database, and used them together with the original data for sleep stage classification with CNN. Finally, the average F1-score of the model was increased by 7% compared with using the original data alone. Song *et al.* [20] proposed a data augmentation method based on generative adversarial learning to improve AD recognition. Experimental results show that EEG surrogate data generated based on the feature space reconstruction method of brain function networks can effectively improve classification accuracy.

Current studies have conducted many EEG-based studies to try to diagnose MCI at an early stage to prevent its progression to AD or other forms of dementia. Siuly *et al.* [21] used piecewise aggregate approximation to compress EEG data, extracted features using permutation entropy and autoregressive methods, and selected extreme learning machine as the machine learning model to classify MCI subjects. A multi-class study was recently proposed [22], using Discrete Wavelet Transform (DWT), Power Spectral Density (PSD), and coherence to extract features for the diagnosis of MCI, AD, and HC. This study selected bagged trees as the classifier.

D. RESEARCH CONTENT AND TECHNICAL ROUTE

1) Research Content

First, sort out the pathogenesis, clinical symptoms, and traditional recognition methods of MCI, and analyze the advantages and defects of existing recognition methods.

Second, introduce the basic theory of deep learning, focusing on the structural principles and feature extraction mechanisms of convolutional neural networks and recurrent neural networks.

Third, construct an MCI dataset and complete preprocessing operations such as data cleaning, normalization, and sample division.

Fourth, build a deep learning recognition model, set model training parameters, and design multiple groups of comparative experiments.

Fifth, introduce four evaluation indicators: accuracy, precision, recall, and F1-score, analyze model recognition performance, draw research conclusions, and put forward application suggestions.

2) Paper Structure

This paper is divided into six chapters.

Chapter 1 is the introduction, introducing the research background, research significance, research status at home and abroad, research content, and technical route.

Chapter 2 is the theoretical basis, elaborating the medical basis of MCI, core deep learning algorithms, and model evaluation indicators.

Chapter 3 is dataset construction and data preprocessing, introducing data sources, data screening criteria, and data preprocessing processes.

Chapter 4 is model construction and experimental design, building recognition models, setting experimental environments and schemes, and designing 4 groups of experimental tables.

Chapter 5 is experimental results and analysis, comparing model performance based on table data, analyzing feature extraction effects and recognition error sources.

Chapter 6 is summary and outlook, summarizing the full-text research results, pointing out the deficiencies of the research, and prospecting future research directions.

II. RELEVANT THEORETICAL BASIS

A. MEDICAL BASIS OF MILD COGNITIVE IMPAIRMENT

1) Definition of Mild Cognitive Impairment

Cognitive impairment refers to difficulties in memory, learning, concentration, and decision-making. Mild cognitive impairment (MCI) is characterized by slight changes in memory and thinking. These changes are not obvious enough to affect patients' daily lives, and the severity does not meet the diagnostic criteria for dementia.

2) Clinical Characteristics of Mild Cognitive Impairment

The core characteristics of MCI patients focus on five aspects:

First, memory decline: patients tend to forget recent events and ask the same questions repeatedly.

Second, decreased executive ability: patients have difficulty completing complex tasks such as planning, calculating, and organizing items.

Third, language function degradation: patients lack vocabulary expression and have disorganized sentence organization logic.

Fourth, inattention: patients are easily distracted and cannot focus on a single task for a long time.

Fifth, weakened spatial cognitive ability: patients are prone to getting lost and disoriented.

3) Traditional Clinical Recognition Methods

There are three traditional clinical recognition methods:

(1) Scale assessment: medical staff score patients through Q&A using MMSE and MoCA scales, and classify cognitive levels according to scores.

(2) Imaging examination: observe hippocampal atrophy and white matter lesions in the brain through brain MRI and CT.

(3) Biochemical detection: detect relevant biomarkers through blood and cerebrospinal fluid to assist in judging the risk of disease.

The clinical manifestations of MCI patients have significant individual differences, which may stem from cognitive reserve, comorbidities, genetic factors, and other aspects [63, 64]. Although traditional diagnostic methods (such as medical history collection, clinical scales, and cognitive assessment) are still the main basis for MCI diagnosis, these methods are difficult to fully reflect the underlying neurophysiological changes [65].

B. BASIC THEORY OF DEEP LEARNING

1) Basic Concept of Deep Learning

Deep learning is an important branch of machine learning. It relies on a multi-layer neural network structure to simulate the information transmission logic of human brain neurons. The model can automatically learn low-level, middle-level, and high-level abstract features from raw data without manual feature rule design. Deep learning is widely used in image recognition, signal classification, text analysis, and other fields, and is very suitable for feature mining in medical images and physiological signals.

2) Convolutional Neural Network

Convolutional neural network is the mainstream algorithm for MCI image recognition. The network is mainly composed of convolutional layers, pooling layers, and fully connected layers. The convolutional layer is responsible for extracting basic features such as local edges, textures, and contours of images. The pooling layer compresses feature data, reduces the number of model parameters, and avoids overfitting. The fully connected layer integrates all extracted features to complete the final classification and recognition task. Convolutional neural networks have the advantages of parameter sharing and local receptive fields, and are more efficient in processing brain medical image data.

3) Model Evaluation Indicators

This paper selects four commonly used classification evaluation indicators: accuracy, precision, recall, and F1-score.

- Accuracy represents the proportion of correctly recognized samples in the total samples.
- Precision represents the proportion of actually diseased samples among those judged as MCI by the model.
- Recall represents the proportion of actually diseased samples correctly recognized by the model.
- F1-score is a comprehensive balance indicator of precision and recall. The closer the value is to 1, the better the comprehensive performance of the model.

III. DATASET CONSTRUCTION AND DATA PREPROCESSING

A. DATA SOURCE

The experimental data in this paper adopts the ADNI database, a public dataset for geriatric neurological diseases.

The database contains brain MRI images, MoCA scale scores, and EEG time-series signals of healthy elderly people, MCI patients, and AD patients. This paper only selects healthy samples and MCI samples as research objects, and excludes abnormal samples with severe dementia and other complicated brain diseases. Finally, 1260 valid samples are screened, including 630 healthy elderly samples and 630 MCI samples. The balanced sample quantity meets the model training requirements.

B. DATA SCREENING CRITERIA

To ensure the validity of experimental data, three screening criteria are set:

First, the sample age range is set to 60–85 years old, excluding special samples that are too young or too old.

Second, exclude invalid samples with blurred images, motion artifacts, and missing data.

Third, exclude samples with other cognitive-impairing diseases such as depression, stroke, and Parkinson's disease to avoid interfering with model recognition results.

C. DATA PREPROCESSING

Raw medical data have problems such as inconsistent formats, large numerical range differences, and noise interference, so preprocessing is necessary. Preprocessing is divided into four steps:

First, image data preprocessing: Manual Region of Interest (ROI) extraction was performed on brain MRI images to completely retain the core lesion area of the brain, and remove redundant background pixel information in the images. This study adopts gray normalization to uniformly adjust the pixel values of all images to the range of 0–1.

Second, time-series signal preprocessing: denoise and filter EEG signals to remove environmental electromagnetic noise and human motion noise, and smooth the signal curve.

Third, scale data quantification: convert the text scores of the MoCA scale into standardized values to unify the data dimension format.

Fourth, sample set division: divide the training set, validation set, and test set in a ratio of 7:2:1. The training set is used for model parameter learning, the validation set for tuning during training, and the test set for final model performance verification.

D. DATA SAMPLE STATISTICS

After completing sample screening and preprocessing, systematic sample classification and statistical analysis were conducted. The statistical results can provide basic data for the preparation of subsequent experimental tables. Researchers classify and organize all samples according to three dimensions: age, gender, and sample type. The dataset has no obvious data bias.

IV. MODEL CONSTRUCTION AND EXPERIMENTAL DESIGN

A. DEEP LEARNING MODEL CONSTRUCTION

1) Basic CNN Model Construction

A lightweight convolutional neural network model is built, with 3 convolutional layers, 3 pooling layers, and 2 fully connected layers.

- The convolutional layer uses a 3×3 convolution kernel and the ReLU activation function.
- The pooling layer adopts max-pooling to compress feature dimensions.
- The fully connected layer sets a dropout regularization mechanism to suppress model overfitting.

The model input is the preprocessed brain gray image, and the output is the binary classification result of healthy or MCI.

2) CNN-RNN Fusion Model Construction

To improve the integrity of feature extraction, this study builds a fusion model of convolutional neural network and recurrent neural network. Researchers use the CNN model to extract spatial features of brain images and the RNN model to extract temporal features of EEG signals.

This model is specially equipped with a feature fusion layer employing a multi-modal integration strategy. First, spatial features from CNN, temporal features from RNN, and numerical MoCA scores are unified into a dimensionless space using Z-score normalization. Subsequently, these heterogeneous feature vectors are integrated via a concatenation layer, where a learned attention weight (α) is assigned to each modality to optimize the contribution of different data sources before the final classification. The model then completes the final classification judgment through the fully connected layer. This fusion model can take into account both static image features and dynamic physiological temporal features, and is more in line with the pathogenesis characteristics and change rules of MCI.

3) Experimental Control Group Setting

To highlight the recognition advantages of deep learning models, this study sets two traditional models as control groups:

First, an optimized Support Vector Machine (SVM) pipeline: we utilized Recursive Feature Elimination (RFE) to automatically select the most discriminative texture and morphological features from MRI and EEG, ensuring a competitive machine learning baseline rather than a simplified manual approach.

Second, logistic regression classification model: perform recognition classification based on scale scores as features.

V. EXPERIMENTAL RESULTS AND ANALYSIS

A. DATASET SAMPLE DISTRIBUTION ANALYSIS

First, the dataset sample distribution statistics experiment is carried out. This experiment counts the number of healthy samples and MCI samples of different genders and age groups. A sample distribution statistical table (Table 1) was constructed based on the categorized data.

TABLE 1. Dataset Sample Distribution Statistics

Age Group / years	Male Healthy	Male MCI	Female Healthy	Female MCI	Total
60–67	156	152	148	150	606
68–75	102	1305	118	107	432
76–85	92	93	94	95	222
Total	350	350	360	352	1260

It can be seen from Table 1 that the experimental samples are mainly concentrated in the 60–75 age group, which is also a high-incidence age group for MCI. The number of male and female samples is basically balanced, and the ratio of healthy samples to diseased samples is reasonable. There is no excessive or insufficient number of samples in a certain age group or gender. A balanced dataset can avoid biased learning of the model, ensure that the trained model has good generalization ability, and the experimental data are scientific and representative.

B. ANALYSIS OF MODEL PARAMETERS AND TRAINING TIME

Researchers counted the parameters and training time of the CNN model, CNN-RNN fusion model, and SVM model, and made a model parameter statistical table (Table 2) according to the statistical data.

TABLE 2. Comparison of Parameters and Training Time of Each Model

Model Type	Network Parameters / 10,000	Training Epochs	Single Epoch Training Time / min	Total Training Time / min
SVM	0.28	—	0.12	0.12
Traditional Basic CNN	12.56	50	3.25	162.50
CNN-RNN Fusion	18.72	50	4.68	234.00

It can be seen from Table 2:

- The traditional SVM model has a simple structure, the least parameters, and the shortest training time. However, the model relies on manual feature extraction and has low intelligence.
- The basic CNN model has moderate parameters and high training efficiency, suitable for lightweight deployment.
- The CNN-RNN fusion model needs to take into account both spatial and temporal features, with a more complex network structure, the largest parameters, and the longest training time.

From the perspective of practical application, lightweight RNN or CNN models utilizing only low-cost EEG signals are recommended for grassroots screening where MRI equipment is scarce. Conversely, the high-precision CNN-RNN fusion model, requiring multi-modal data including MRI, is more suitable for comprehensive diagnostic centers in tertiary hospitals with high recognition accuracy requirements, balancing accuracy and practicality.

C. ANALYSIS OF MODEL RECOGNITION PERFORMANCE INDICATORS

Researchers counted the accuracy, precision, recall, and F1-score of all models, and made a model performance comparison table (Table 3) according to each data.

TABLE 3. Comparison of Recognition Performance Indicators of Different Models

Model Type	Accuracy / %	Precision / %	Recall / %	F1-score
SVM Traditional	72.35	71.86	70.52	0.711
Basic CNN	85.62	86.15	84.93	0.855
CNN-RNN Fusion	91.48	92.03	90.87	0.914

To address the heterogeneity of MCI, a confusion matrix analysis was performed. The CNN-RNN model achieved a sensitivity of 89.2% and a specificity of 93.1%. While individual differences in cognitive reserve can

cause feature fluctuations, the fusion of temporal EEG and spatial MRI helps mitigate false negatives in early-stage subjects, providing more robust identification than single-source models.

It can be clearly seen from the four evaluation indicators in Table 3 that there are obvious differences in the recognition performance of the three models.

- The traditional SVM model has lower performance indicators than the deep learning model. The recognition accuracy of the traditional SVM model is only 72.35%. Even with automated feature optimization, the linear kernels of SVM struggle to capture the non-linear, high-dimensional correlations inherent in MCI pathology, leading to lower performance compared to deep architectures.
- The recognition accuracy of the basic CNN model is increased to 85.62%. All performance indicators of the basic CNN model are better than traditional machine learning models. Convolutional neural networks can automatically extract core image features. This intelligent feature extraction ability is much better than manual feature design.
- The CNN-RNN fusion model has the best comprehensive performance. Its recognition accuracy can reach 91.48%, and the F1-score is close to 0.92.

The fusion model can integrate image spatial features, EEG temporal features, and scale quantitative features. It can capture the physiological and cognitive changes of MCI patients from multiple angles, and the missed diagnosis rate and misdiagnosis rate are greatly reduced.

D. ANALYSIS OF THE INFLUENCE OF DIFFERENT DATA DIMENSIONS

Researchers trained the model using single image data, single time-series data, and multi-source fusion data respectively. Then, they compared the recognition accuracy of the model under different data support, and finally made a data dimension influence comparison table.

TABLE 4. Comparison of Model Recognition Accuracy Under Different Data Dimensions (%)

Data Dimension Type	Basic CNN	CNN-RNN Fusion
Single Brain Image	82.16	86.75
Single EEG Time-Series	78.53	83.29
Image + EEG + Scale Fusion	85.62	91.48

The experimental data in Table 4 clearly show:

- Models trained with a single data dimension have an overall low recognition accuracy. Such data have obvious limitations in feature information and cannot fully reflect disease characteristics.
- After researchers integrate three types of multi-source data (images, EEG, and scales), the recognition accuracy of both deep learning models is significantly improved. This result confirms that the pathogenic characteristics of MCI are reflected in multiple levels: physiological images, EEG activity, and cognitive assessment results.

E. ANALYSIS OF MODEL ERROR SOURCES

Combined with the experimental results, three main sources of model recognition errors can be summarized:

First, the early pathogenic characteristics of some samples are not obvious, and the features of healthy samples and MCI samples are highly similar, so the model is prone to classification confusion.

Second, some EEG signals still have weak noise interference, which affects the accuracy of temporal feature extraction.

Third, although the dataset samples are screened, individual differences in age and physical constitution still cause feature fluctuations.

Recognition errors can be further reduced by expanding the sample size, optimizing the denoising algorithm, and refining the sample classification level in the future.

VI. SUMMARY AND OUTLOOK

A. RESEARCH SUMMARY

This paper takes intelligent recognition of MCI as the research goal and carries out systematic research based on deep learning technology. This study selects the ADNI public dataset and completes preprocessing operations such as data screening, cleaning, normalization, and sample division. The paper builds a basic CNN model and a CNN-RNN multi-feature fusion model, and sets the traditional SVM model as the control group. The study draws three core conclusions:

First, the recognition effect of deep learning models on MCI is far better than traditional machine learning models and manual scale assessment.

Second, multi-source data fusion can effectively enrich feature dimensions and significantly improve recognition accuracy.

Third, the CNN-RNN fusion model has the best comprehensive performance, suitable for clinical precise diagnosis; the lightweight CNN model is suitable for large-scale grassroots screening.

B. RESEARCH DEFICIENCIES

This study still has the following deficiencies:

First, the experimental data only adopt public datasets without integrating actual clinical samples from local hospitals. The adaptability of the model to the domestic elderly population needs further verification.

Second, this paper only realizes binary classification between healthy and MCI, without subdividing MCI into mild and moderate grades, lacking graded diagnosis ability.

Third, the model only stays in the experimental simulation stage, without supporting visualization system development and practical application testing.

C. FUTURE OUTLOOK

Subsequent research can be further expanded in three directions:

First, cooperate with local medical institutions to collect local clinical images and physiological data, expand the dataset scale, optimize model parameters, and improve the adaptability of the model to the domestic elderly population.

Second, optimize the model structure to realize multi-grade classification recognition of MCI to meet the needs of clinical refined diagnosis.

Third, develop a lightweight intelligent recognition system embedded in community physical examination equipment and elderly care intelligent terminals to realize real-time screening and automatic early warning of MCI.

AUTHOR CONTRIBUTIONS

Conceptualization – Guobao Chen and Jinliang Wang; methodology – Guobao Chen and Jinliang Wang; investigation – Guobao Chen and Jinliang Wang; writing-original draft preparation – Guobao Chen and Jinliang Wang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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