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# Progress in the Application of Deep Learning Combined with fNIRS in MCI Research

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**Abstract:** With the continuous development of functional near-infrared spectroscopy, (fNIRS) and deep learning technology, the fusion of deep learning with FNIRS is increasingly being utilized in research on MCI. This paper begins by outlining the basic principles of FNIRS and the fundamental concepts of deep learning required for fusion. It then summarizes the analysis methods and latest findings of deep learning fused with FNIRS in MCI research, and explores its future development direction.

**Keywords:** MCI; fNIRS; Deep-Learning; CNN.

## 1. Introduction

Alzheimer's disease ,(AD) is the most prevalent form of dementia, frequently manifesting in older adults and early seniors[1]. It is characterised by progressive cognitive impairment and behavioural deterioration, and is a degenerative disease of the central nervous system[2]. From a clinical perspective, the condition is characterised by a range of cognitive impairments, including memory impairment, aphasia, apraxia, agnosia, visuospatial impairment, impaired abstract thinking and calculation abilities, and personality and behavioural changes[3].As our understanding of AD has evolved, it has become evident that the disease has been progressing for decades before the onset of cognitive impairment is detected. Clinically, the initial presentation of AD is as mild cognitive impairment, (MCI), due to the underlying pathology of AD. This then progresses to dementia[4]. Consequently, the identification and detection of MCI is of significant importance. The advent of neuroimaging techniques has led to the identification of an increasing number of abnormal images prior to the manifestation of clinical symptoms. Among these, MRI scans are particularly effective, but they are difficult and costly to perform, have low tolerance for motion artefacts, and low temporal resolution. Recent years have seen an increased interest among researchers in the field of fNIRS. The neurovascular coupling hypothesis forms the theoretical foundation for the utilisation of fNIRS in the investigation of cerebral function. The underlying principle of fNIRS entails the measurement of the absorption and scattering of near-infrared light within the brain tissue, thereby facilitating insights into the complex dynamics of neural activity[5]. As a non-invasive brain imaging technique, it offers advantages such as high temporal resolution, low cost, high tolerance to motion artefacts, and ease of use, and is increasingly being applied in the detection of neuropsychiatric disorders[6]. Despite its comparatively low spatial resolution, recent advancements in initial tilt detection, optoelectronic device integration, and adaptive algorithms have enhanced the spatial resolution of fNIRS. This has resulted in a significant increase in the interest surrounding fNIRS in academic research, leading to its widespread utilisation in both neuroscience research and clinical practice. Deep learning, (DL) is a subfield of traditional machine learning, (ML). In recent years, with the enhancement of computing capabilities and the proliferation of medical equipment and digital record systems, deep learning has witnessed an escalating application in medical research, particularly in the domain of medical image analysis employing CNN, (convolutional neural networks). The utilisation of deep learning models, incorporating convolutional neural networks, to analyse detected fNIRS signals, has been demonstrated to facilitate the identification and detection of MCI[7]. This paper introduces the relevant concepts and basic processes of deep learning, reviews the research progress of deep learning fusion and FNIRS in MCI, and discusses its development direction.

## 2. Basic Concepts of Deep Learning

**Machine learning, (ML):** A subset of artificial intelligence, it is essentially a mathematical model based on sample data. Its core idea is to enable computer systems to learn from data and make predictions or decisions based on the knowledge they have learned. Data sets are typically divided into training sets, validation sets, and test sets.

Training set: Data that the model has 'seen' and is used to train the model's parameters.

Validation set: Data that the model has not seen before, used to adjust the model's hyperparameters.

Test set: Used for final evaluation of model performance.

Parameters: Variables within a model that can be learned and optimised through training data.

**Deep Learning, (DL):** A machine learning model with multiple hidden layers, essentially a large set of functions that can be trained on a large scale to extract feature information, achieving significant accomplishments in text and image recognition. Based on network structure, DL models are categorised into feedforward neural networks, (FNN), convolutional neural networks, (CNN), recurrent neural networks, (RNN), autoencoders, (Autoencoders), and generative adversarial networks, (GAN). This article focuses on CNN and RNN.

Convolutional Neural Networks, (CNN): These networks have representation learning capabilities and can perform translation-invariant classification of input information according to their hierarchical structure. They are mainly used in image processing to solve computer vision problems.

Recurrent Neural Network, (RNN): Has memory capabilities and can perform recursion on sequence data, making it suitable for processing sequence data.

**Common steps in deep learning:** data preprocessing, feature extraction, model training, and five-fold cross-validation.

Data preprocessing: Converting raw data into a format suitable for model training, such as converting it into a statistical activation map for CNN training. This can improve model performance and reduce overfitting.

Feature extraction: Extract effective features from raw data to help the model learn patterns and rules in the data. In deep learning, feature extraction is usually not required manually.

Model training: Train deep learning models using datasets and update model parameters through the backpropagation algorithm.

Five-fold cross-validation: Used to evaluate model performance and adjust model hyperparameters.

# 3. Application of fNIRS-Deep Learning in MCI

Yang et al. used fNIRS to collect data from 24 subjects, (including 15 MCI patients and 9 cognitively normal subjects) while they performed N-back, (refresh task), Stroop, (Stroop paradigm task), and VFT, (verbal fluency task) tasks. After preprocessing the data, ROI analysis was used to select regions active during psychological tasks. A convolutional neural network was employed to train the model across three features: temporal, spatial, and temporal-spatial, (spatio-temporal). The model training results were evaluated using five-fold cross-validation.[Time characteristics refer to the original 1HbO of the time series, spatial characteristics refer to brain maps generated at specific points in time, and spatiotemporal characteristics refer to neuroimaging based on time characteristics ,(mean, slope value, skewness, kurtosis) over a specific period of time[8].] The results of model identification for MCI patients under different cognitive tasks are shown in Table 1, with the values representing accuracy rates. The spatial features and spatiotemporal features are averaged. The results indicate that spatiotemporal feature neuroimaging has a high prediction accuracy rate and can be used to assist in the clinical diagnosis of MCI.

**Table 1.** Accuracy under different features

| Feature | N-back (%) | Stroop (%) | VFT (%) |
|---|---|---|---|
| Time | 77.9 | 84.70 | 77.84 |
| Spatial | 82.59 | 85.03 | 82.20 |
| Spatiotemporal | 89.46 | 87.80 | 90.37 |

Zhang et al. obtained fNIRS data from 154 participants, (including cognitively normal individuals and those with mild cognitive impairment, (MCI)) during the Stroop task using a 70-channel continuous near-infrared spectroscopy, (Nirsmart) system. They preprocessed the data using a standardised near-infrared spectroscopy preprocessing method summarised from their own experiments. Ultimately, data from 127 participants were retained, and feature extraction was performed on these data. The feature extraction results were categorised into four types: Tpoint HbO, Tpoint HbR, Tstat Hbo, and Tstat HbR. Each extracted feature was rearranged into 1D, 2D, and 3D shapes, ultimately yielding one-dimensional channels, 2D spatial features, and 3D spatiotemporal features of the near-infrared spectroscopy signals. They used 1D MLP, 2D CNN, and 3D CNN models with automatic hyperparameter tuning based on Bayesian optimisation to train models for the corresponding features, and evaluated the model training results using five-fold cross-validation. The average accuracy rates for identifying MCI individuals across the four features for the three models are shown in Figure 2, indicating that 3D tPOINT HbO achieved the best classification performance[9].

**Table 2.** Accuracy rate in different dimensions

| | Tpoint HbO (%) | Tpoint Hb (%) | Tstat Hb (%) | Tstat HbR (%) |
|---|---|---|---|---|
| 1D | 59.17 | 58.69 | 57.83 | 58.83 |
| 2D | 62.75 | 57.25 | 60.15 | 56.92 |
| 3D | 73.85 | 61.59 | 63.85 | 60.77 |

Ma et al. divided the 140 subjects into four stages. HC, (normal), aAD, (asymptomatic AD), pAD, (mild cognitive impairment), and ADD, (AD dementia). The subjects were administered a series of cognitive assessments, including the Oddball test, (cognition), the 1-back test, (memory), and the Verbal test, (language), in a sequential manner across four distinct subject groups. The collection of participants' cerebral oxygen concentration data was facilitated by the use of functional near-infrared spectroscopy, (fNIRS). Four deep learning models were utilised for the training process: CNN, (one-dimensional), LSTM, (long short-term memory network), GRU, (gate recurrent unit), and CNN-LSTM. These models were applied to fNIRS data for multi-level classification to identify AD patients at different stages, and five-fold cross-validation was used to evaluate the model training results. ,(RNN can be used for the processing of sequence data, and LSTM is a special type of RNN network that can be used to distinguish changes in the feature space of fNIRS data at different stages of AD.) The findings demonstrated that the CNN-LSTM model attained prediction accuracies of 91.6%, 87.7%, 88%, and 79.7% for HC, aAD, pAD, and ADD, respectively, which exceeded those of the other three deep learning models. In addition, the model exhibited superior performance in comparison with seven other machine learning algorithms, thus justifying its designation as a useful tool for assisting clinicians in the grading assessment of AD[10].

As demonstrated in preceding studies, heightened cognitive demands in cognitively normal individuals have been shown to be accompanied by increased prefrontal activity [11]. Park utilised functional near-infrared spectroscopy, (fNIRS) to monitor the prefrontal haemoglobin oxygen levels, (HbO) of 120 subjects with mild cognitive impairment, (MCI) as they performed three cognitive tasks of varying difficulty, (0-back, 1-back, and 2-back). The HbO values of eight channels were then plotted to create statistical activation maps. He used five-fold and ten-fold cross-validation to test the accuracy of predicting HbO statistical activation maps for different levels of cognitive tasks, with accuracy rates of 91.25% and 93.33%, respectively. The results indicate that fNIRS can be used to measure mental load in patients with MCI[12].

During the training process of deep learning models, an insufficient dataset can result in issues such as overfitting and local minima during training. Moreover, it has been demonstrated that cognitive tasks which extend over a protracted period may occasion patient fatigue, with the consequence that the reliability of the test is diminished. Yang and Hong utilised a multi-channel NIRSIT continuous wave system to extract near-infrared light data from 24 subjects, (15 with MCI and 9 cognitively normal individuals) during 9 different resting periods with the objective of identifying MCI and verifying the minimum duration required for resting state data. They generated connection diagrams from this data and used pre-trained CNN models to perform feature representation-based transfer learning on these connection diagrams, (transfer learning avoids the problems of overfitting and low generalisation ability that arise when training models with small data sets). The extracted features were then entered into a Support Vector Machine, (SVM) for model training, with five-fold cross-validation being utilised to assess the efficacy of the model training process. The findings indicated that the mean accuracy of HbO attained its zenith at a measurement interval of 30 seconds, achieving 81.27% precision[13].

**Table 3.** Summary of experiments

| Reference | Subjects | Channels | Brain regions | Tasks | Analytical methods |
|---|---|---|---|---|---|
| Yang et al. | 24 | 48 | PFC | N-back, Stroop, VFT | Use CNN to perform convolution on three features—time, space, and spatiotemporal—to find reliable markers. |
| Zhang et al | 154 | 70 | PFC, PL | Stroop | Using Bayesian-based automatic parameter tuning for 1D MLP, 2D CNN, and 3D CNN networks to identify MCI patients separately. |
| Ma et al | 140 | 8 | PFC | Oddball, 1-back, Verbal | Using CNN, LSTM, GRU, and CNN-LSTM for multi-level classification of FNIRS data to identify AD patients at different stages |
| Park | 129 | 8 | PFC | 0-back, 1-back, 2-back | Using CNN to identify statistical activation maps of HbO under different levels of cognitive difficulty |
| Yang, Hong | 24 | 48 | PFC | Resting state measurement | Using pre-trained CNNs for transfer learning on connected graphs to assist SVM model training |

# 4. Conclusion

The affordability, accessibility and tolerance for motion artefacts of fNIRS facilitate the acquisition of substantial brain data sets. When combined with deep learning algorithms, it can efficiently process and analyse large-scale brain data. Concurrently, deep learning models have the capacity to extract features and classify complex FNIRS data, thereby enhancing the utilisation rate of fNIRS data and providing a novel perspective for the early diagnosis of MCI. However, fNIRS combined with deep learning also has certain limitations in its application: (1) fNIRS is mainly used to measure changes in blood oxygen levels on the surface of the cerebral cortex and has relatively weak imaging capabilities for deep brain regions. ,(2) Compared with functional magnetic resonance imaging, (fMRI), fNIRS has lower spatial resolution and limitations in studying specific areas of brain activity. ,(3) fNIRS data must be analysed in combination with physiological and optical principles, which makes the interpretation of fNIRS data complex., (4) Deep learning models require a huge amount of data.

Given these limitations, future research could integrate other neuroimaging techniques for multimodal imaging, such as fMRI and electroencephalography, (EEG), to obtain higher-resolution, more comprehensive data on brain activity. Combining physiology and computational models, develop automated fNIRS data processing and analysis tools to obtain more accurate brain activity information. Establish a globally shared fNIRS database to provide a large dataset for the establishment of deep learning models. It is imperative to undertake further optimisation of the structure and hyperparameter settings of deep learning models, with a view to enhancing their reliability and usability in clinical practice.

In summary, the combination of functional near-infrared spectroscopy fNIRS with deep learning technology holds considerable potential in the field of MCI research. This integration offers significant support for the early diagnosis and personalised treatment of Alzheimer's disease, thereby promoting the advancement of brain science and neurology.

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