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Application analysis of deep neural network in prediction of Alzheimer's disease*

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Abstract: A comprehensive review of deep neural network methods in the classification and prediction of Alzheimer's disease is presented. Firstly, the advantages of deep neural network method in the classification and prediction of Alzheimer's disease is described. Secondly, the application of deep neural network method in the classification and prediction of Alzheimer's disease is introduced. The deep neural network model, data types, research population and feature types used in the literature are introduced, and compare their performance in the AD/MCI classification. Finally, the future development trends and challenges in the field are predicted.

Key words: Alzheimer's disease; convolutional neural network; deep belief network; neuroimaging

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0 Introduction

Alzheimer's disease (AD) is a neurodegenerative disease that causes progressive loss of memory, speech impairment, and fuzzy thinking. With an aging society in the speed, the number of older people with AD will increase. China's Alzheimer's disease is expected to exceed 20 million in the world by the year 2050[1]. In fact, the brain structure of patients has changed before memory decline[2], and these changes usually occur in temporal lobe and hippocampus[3]. Studies have shown that this change can be used as a biomarker of neurodegeneration[4], which can be measured by structural magnetic resonance imaging (sMRI). Under the influence of AD, not only the brain structure will change, but also the functional connections and metabolism in the brain will change. These changes can be further detected by functional magnetic resonance imaging (fMRI) and fluorodeoxyglucose positron emission tomography (FDG-PET)[5-10]. However, the changes in the early stages of AD are very subtle and difficult to distinguish by conventional radiological readings or quantitative analysis. Therefore, it is very important to establish a reliable AD computer-aided diagnosis system by analyzing neuroimaging or biomarkers of different modalities.

In recent years, many studies on neuroimaging have studied subtle changes associated with AD by analyzing regions of interest (ROI)[11]. Such studies ignore brain changes outside of ROI and rely only on prior knowledge to guide ROI and feature selection. Machine learning provides a systematic approach to developing complex automated classification frameworks, analyzing high dimensional data and learning the complex and subtle changes in various neuroimaging modalities[12]. Therefore, many studies have used machine learning methods (such as support vector machine[13], independent component analysis[14], Bayesian meth-

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od[15] and penalty regression[16]) to analyze the neuroimaging data of the subjects, thus establishing a set of their own classification framework for MCI conversion prediction and AD/MCI/NC classification[17-24], as shown in the table1. Traditionally, representative or task-related features rely primarily on prior knowledge to design, thus making it difficult for non-experts to use machine learning for their own research. However, deep learning[25] can automatically learn representative features to solve these obstacles, that is, deep learning can eliminate the need to manually extract features. As a result, today's computers can perform feature extraction tasks brilliantly, which allows experts who are not good at machine learning to use deep learning in their research (especially in medical image analysis) as they please.

Table 1 Some studies on the early diagnosis of Alzheimer's disease

Study	Modal	Feature	Classification algorithm	Dataset	Number of images (AD/NC)	Classifcation accuracy(AD vs. NC)
Klppel[17] 2008	sMRI	Tissue density	SVM	RM	33/57	81.10
Par[18] 2013	sMRI	Cortical thickness	SVM	OASIS	25/50	90.00
Nir[19] 2015	DTI	Tractography	SVM	ADNI	37/50	80.60
Vandenberghe[20] 2013	PET	VAF	SVM	Internal	27/25	88.46
Casanova[21] 2011	sMRI	Tissue density	LSR	ADNI	49/49	85.70
Cho[22] 2012	sMRI	Cortical thickness	LDA	ADNI	128/160	88.33
Wee[23] 2013	sMRI	Cortical thickness	Multi-kernel SVM	ADNI	198/200	92.35
Chen[24] 2011	fMRI	Functional connection strength	Fisher LDA	MDC	20/20	82.00

RM=Rochester, Minnesota, USA
OASIS=Open access series of imaging initiative
MDC=Memory disorders clinic, Medical College of Wisconsin, Milwaukee, Wisconsin, USA

There are three conditions necessary for deep learning to achieve unprecedented success. The first is the rapid development of high-tech central processing units (CPUs) and graphics processing units (GPUs), the second is the emergence of large-scale available data sets, and the third is the development of learning algorithms[26-29]. Deep neural networks consist of multiple (more than two) layers of networks that improve traditional artificial neural networks[30]. In terms of the input types, we can categorize deep models as typical multi-layer neural networks that take input values in vector form (i.e., non-structured) and convolutional networks that takes 2D or 3D shaped (i.e., structured) values as input. Deep convolutional networks are now the technology of choice for computer vision. Not only has CNN been successfully applied in AD classification research, but also the network with vectorized input has been successfully applied to AD classification research[41-49,51-52]. With the development of the depth generation model[31], probabilistic graphical models with multiple hidden variables (such as deep belief networks and deep Boltzmann machines) have also been successfully applied to AD classification diagnosis[48,49,51,52].

The number of papers in the AD diagnosis/classification using deep neural networks increased rapidly between 2015 and 2018. To determine the relevant contributions, it searched the Google Scholar and PubMed online databases for papers that included “Convolutional Neural Networks” or “Deep Learning” and “AD Diagnostics” or “AD Classifications” in the title or abstract. It hopes that search keywords will cover most, if not all, of the work involved in deep learning methods.

In the second part, we overview the key representative studies of AD/MCI classification based on neuroimaging data, and briefly introduce and compare the main aspects of these studies, such as the deep neural network model used, data types, research population, feature types and classification performance (accuracy, sensitivity and specificity). Finally, it summarizes the problems and future research directions of deep neural networks in the application of AD/MCI classification.

1 Applications of deep neural network in AD/MCI classification

Large-scale data trainingdeep neural network (DNN) is used to transform raw data into low-level features through nonlinear functions in order to obtain more representative feature representations[32]. The rapid development of the Discovery Science project by Biswal et al.[33] and the brain science programs such as ADNI, OASIS and the Human Connectome Project(HCP)[34] provide the necessary large-scale research for deep learning. The material makes the use of deep neural network methods in brain science research more and more extensive. Compared with traditional machine learning algorithms, deep learning does not necessarily require preprocessing similar to traditional algorithms before the data input model. It can automatically learn features, reduce the subjectivity of feature selection, and shorten the time of previous work. This section outlines the application of stacked autoencoder[39-45], deep confidence network and deep Boltzmann machine[46-49], convolutional neural network[52-57] in AD/MCI classification. The data selection and model methods and classification accuracy of various depth deep neural network models are shown in Table 2.

1.1 Application of vectorized input deep neural network in AD/MCI classification

1.1.1 Application of stacked automatic encoder (SAE) in AD/MCI classification

Studies have shown that the integration of complementary knowledge from different modalities can help distinguish between AD/MCIs and healthy controls (HC)[35], and many studies have supported this assertion[36][37]. However, Suk et al.[38] considered that previous literature only used some shallow low-level features such as the gray matter volume of MRI, the average signal intensity of PET, and the biometric measurement of cerebrospinal fluid (CSF), potential advanced information that exists in these original features is not considered. Therefore, Suk et al. used SAE to extract potential feature expressions in MRI and PET data to classify AD/NC, MCI/NC, AD/MCI, MCIc/MCInc. The training model is shown in Figure 1. In the study, the gray matter volume of sMRI and the average signal intensity of PET were first extracted, and then the gray matter volume of sMRI, the average signal intensity of PET, and the raw data of CSF were used as input of SAE. In the model training, combined with the supervised parameter fine-tuning method. Then, the cognitive scores and classification labels are merged with the trained features, and the deep information of the three modes is obtained. Finally, multimodal feature fusion and classification are performed.

Since PET and MRI data have nonlinear characteristics, if only simple feature fusion is performed on them, it is easy to generate a case where only one mode is activated. Therefore, Liu et al.[41] performed AD/MCI classification using the same models and features as Suk et al.[38]. In order to avoid the case where only one mode is activated, after the two modes are pre-trained and feature-extracted separately, a modal input network is randomly selected during feature fusion, the other modality is hidden as a 0 state input. This treatment better stimulates the correlation between different modes.

Most of the experimental data in the above literature comes from the ADNI dataset, and the training sets and test sets used are very maneuverable. Objective comparisons between methods may be obscured due to differences in experimental data and feature extraction, feature selection, and verification methods. Therefore, Dolph et al.[45] used the SAE method to classify AD, MCI and AD on the CAD-Dementia data set. The ADNI class label is controlled by precise thresholding in certain dementia tests and measurements, while the CAD-Dementia class label is specified by a multidisciplinary team and does not use the hardthreshold of the dementia metric, so the classification results are relatively objective. In the study, the fractal dimension (FD) texture property of hippocampus in structural MR images were first extracted, and the GLCM statistical features of (FD) features were calculated to describe the FD feature patterns. Then two different feature selection models are established. Model 1 combines 310 volumes, cortical thickness, and surface area characteristics with 5000 FDCM characteristics. After standardizing the features, the elastic network feature selection is performed. Model 2 used the elastic mesh in Model 1 for feature selection, but did not feature selection for volume, cortical thickness, and surface area measurements. Finally, different SAEs are trained separately for the features selected by Model 1 and Model 2. Both models proposed in the study provide a higher true positive score (TPF) for AD classification than the top-level overall ranking algorithm.

SAE has a more complex hierarchy and better learning ability than traditional neural networks, and has achieved good results in the AD/MCI classification. At present, experts are also working on the improvement of SAE details in order to obtain better classification results.

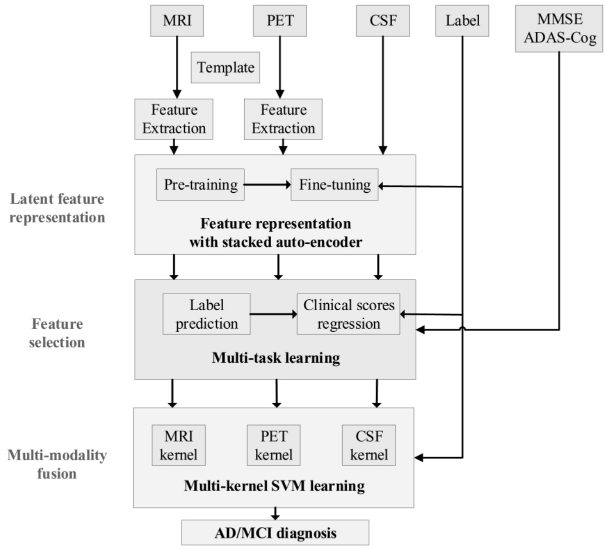

Figure 1　The framework of SAE classification method

1.1.2　Application of deep boltzmann machine (DBM) and deep belief network (DBN) in AD/MCI classification

In 2006, Hinton et al.[26] proposed an unsupervised deep learning algorithm for deep belief network (DBN). The greedy layer-by-layer training algorithm is used to extend the hidden layer in the model to 7 layers through unsupervised layer-by-layer initialization, which solves the problem of deep network training. Brosch T et al.[46] introduced the DBN model into the AD/MCI classification study. It used DBN to reduce the dimension of the input image to perform manifold learning. To extend the pattern to high-resolution images, the begin few layers of the DBN in the study were convolutional RBMs (convRBM), an RBM that uses weight sharing to desrease trainable weights. Due to the large number of trainable parameters, traditionally, the computational cost of DBNs in 3D images has been too high. The main contribution of this research is 1) a DBN training method is more computationally efficient and can train 3D medical images with resolutions up to 128×128×128; 2) the DBN can learn examples of low-dimensional data sets to detect brain volumes of patterns of change associated with demographics and disease parameters. Andr′es Ortiz et al.[47] further used DBN for the AD/MCI classification. A set of weak classifiers is generally considered to be more accurate than a single classifier[33,37]. When the dimension of the feature space is high, using a weak classifier to reduce the number of features can help avoid dimensional disasters. Andr′es Ortiz et al.[47] constructed an integrated DBN to fuse the features of both MRI and PET modes. Different DBNs are trained on each 3D grayscale image block defined by the AAL map and then composed into a deep belief network set. Two classification schemes are proposed in the study, one is a discriminant DBN and a voting method. The other is to use DBN's ability to represent information on different abstraction layers, extract features using DBN and then use SVM for classification. After several experimental analyses in the study, the network was finally set to contain three hidden layers, and the three layers were assumed to be the same size, and each hidden layer contained 400 nodes. Such a setting can effectively reduce the convergence time of the network and limit the number of possible solutions.

In the calculation, the distribution of the DBN lower layer does not depend on the upper layer, while the DBM low-level distribution solution depends on the high-level distribution.

In other words, layer $h1$ of DBN depends on the distribution of layerv, while layer $h1$ of DBM relies on layer $h2$ and layer v at the same time, which makes DBM more robust. Suk et al.[48] used DBM in MCI transformation prediction and classification research, and the proposed DBM classification framework is shown in Figure 2. In this study, 398 subjects were used to segment MRI and PET, and the images of PET and MRI were first divided into several 3D blocks. They are then imported into the DBM model for potential feature extraction to obtain a representation of the characteristics of each stage of the disease. Then carry on the feature fusion and classification recognition of the two modes. The AD/NC, AD/MCI and MCIc/MCInc were classified in the study, and the accuracy rates were 95.35%, 85.67%, and 74.58%, respectively. This study confirms that the DBM network model can be used for MCI classification by the layer-by-layer training method, and some potential features related to AD in MRI and PET can be found.

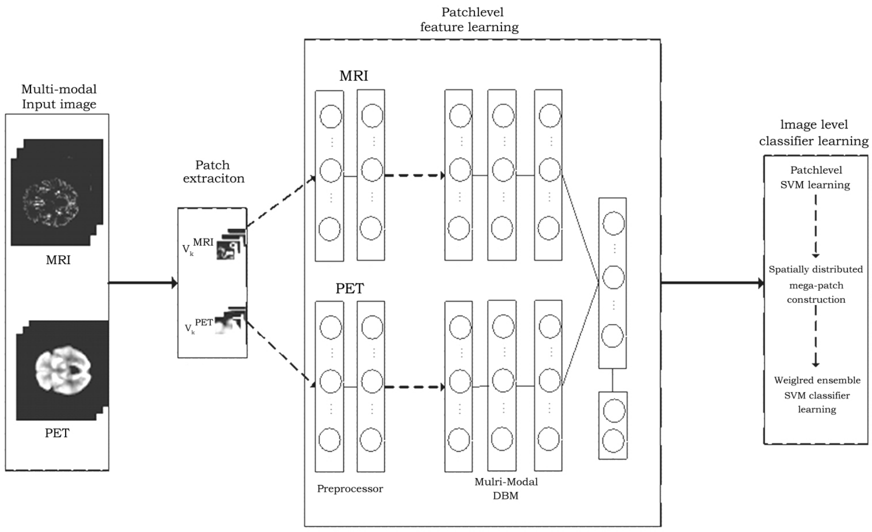

Figure 2 Schematic illustration of the proposed method in hierarchical feature representation and multimodal fusion with deep learning for AD/MCI diagnosis.

Through research, it is found that the number of studies applying DBM and DBN in AD classification is small, and the research scope is narrow. The excellent performance of DBN and DBM has not been fully developed in the AD classification, and it is necessary for the latecomers to continue to explore.

1.2 Application of convolutional neural network algorithm in AD/MCI classification

1.2.1 Application of general CNN model in AD/MCI classification

The inputs to the above models such as SAE, DBN and DBM are always in vector form. However, adjacent pixels or voxels in a medical image also contain a lot of structural information that helps to discriminate AD/MCI/CN. Therefore, vectorized input inevitably destroys structural information in the image. The convolutional neural network (CNN)[50] can take 2D or 3D images as input, which makes better use of space and configuration information. In 2014, Liu et al.[51] selected 600 MRIs in the ADNI database, including 200 subjects in the AD, MCI and NC groups. Liu et al. used the AlexNet structure, which Krizhevsky et al.[19] won in the ImageNet competition, to classify AD/NC, MCI/NC, AD/MCI, AD/MCI/NC, and compare the results. The network model is an 8-layer CNN. As shown in Figure 3, the first five layers are convolutional layers, the last three layers are fully connected layers, and the last classification layer uses the softmax classifier. For the three-dimensional MRI image, the original sMRI is converted into 227×227 pixel resolution and RGB three-channel image input in the first layer of the network. Calculate the characteristics of the MRI image at each layer using a pre-trained network in ImageNet. The features of each layer of MRI images are calculated using a pre-trained network in ImageNet. Finally, based on SVM, the second and third classifications of AD, NC and MCI are performed.

In 2016, Sarraf et al.[52] used the classic LeNet5 and GoogLeNet networks to classify images of AD and NC using functional MRI (fMRI) and sMRI, respectively. The result of classification using preprocessed fMRI data reached 99.9%. According to the difference of smoothing parameters in sMRI preprocessing, this study divides sMRI into 5 groups and inputs two networks respectively, which have obtained good classification accuracy. The accuracy of the highest group obtained by GoogLeNet is 98.84%. Ciprian D et al.[53] improved the 16-layer DemNet and used the 1.5T weighted MRI data of 900 subjects in ADNI for AD, MCI and NC classification. To reduce overfitting, the author added a dropout layer after each pooling layer. The number of nodes in the fully connected layer has also been reduced from 4096-4096-1000 to 256-256-3. Only the accuracy was used to evaluate the classification performance of the three classification models-DemNet, with an overall accuracy of 91.85%.

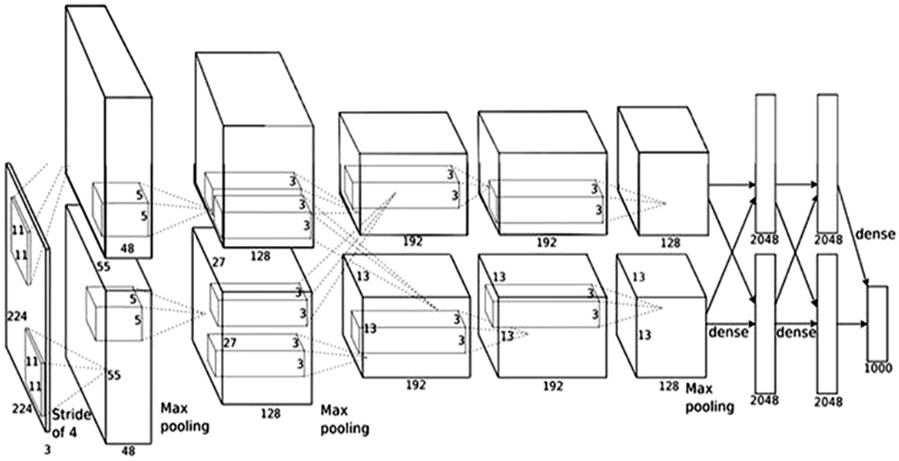

Figure 3　The structure of AlexNet

1.2.2　Application of 3D CNN model in AD/MCI classification

Although the work of Liu et al.[53-55] has obtained good results, there are still some limitations in feature extraction. Since the magnetic resonance image is a 3-dimensional image, a partial slice image of the magnetic resonance image is extracted as input data in the above work, which may lose stereoscopic structure information in the medical image. Since 3D convolutional neural network (3DCNN) CNN and 3D convolution autoencoder (3D CAE) are deep convolution learning models that can extract various image characteristics. Therefore, Li et al.[54] proposed combining 3D CNN and 3D CAE to catch the abundant characteristics of 3D MR images for integrated classification. The 3D CAE structure is shown in Figure 4. The whole process is divided into a pre-training phase and a fine-tuning phase. First, 3D CNN and 3D CAE are separately trained with a fixed size (69 × 59 × 57) 3D MR image as input to capture characteristics of MR images, add a softmax layer to classify with reduced features. Then keep the various parameters of the convolutional layer and the pooled layer unchanged, and fine-tune the parameters of the last convolutional layer and the fully connected layer

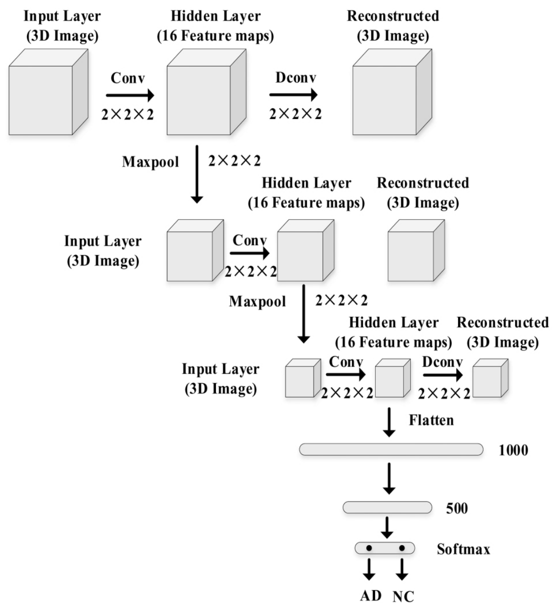

Figure 4　Structure of the 3D convolutional autoencoder autoencoder

for classification of particular tasks. By fine-tuning the tail layers, the model can be more adaptive to classification tasks. Therefore, information in imaging changes and classification tasks can be integrated to help improve classification accuracy. Second, fine-tuning the last few layers significantly reduces computational costs and over-fitting issues compared to training across the network.

1.2.3 Application of transfer learning and CNN in AD/MCI classification

Usually, it takes a lot of time for the medical staff to mark the image, and the training CNN needs to give the label corresponding to the image data, so the number of qualified medical images with detailed label information is relatively rare. In addition to relying on high-quality data, on the other hand, CNN has a high demand for sample size, especially for complex CNN. The number of parameters of complex CNN is usually on the order of 10^7-10^8. Only a sufficient amount of qualified data can train a good model. Therefore, training complex CNN directly with medical image data tends to over-fitting, that is, the network does not extract feature information from the training samples, and the trained model does not have high prediction accuracy for the verification data set. As a result, some scholars have published many books on the problem of medical image samples. Jyoti Islam et al.[55] used three DenseNet[56] models-DenseNet-121, DenseNet-161 and DenseNet-169 integration for the Alzheimer's disease detection and classification framework. The concept of Transfer learning is introduced in this paper. The DenseNet-121, DenseNet-161 and DenseNet-169 models are pre-trained in the ImageNet dataset, where the numbers 121, 161 and 169 represent the depth of the model. The input data is the axial or horizontal plane of the MRI image, the coronal or frontal plane, and the sagittal or medial plane. The test results in the OASIS data set show that the accuracy of the proposed method reaches 93.18%.

1.2.4 Application of CNN based on multimodal image in AD/MCI classification

Table 2 Application of deep neural network algorithm in AD/MCI classification forecasting

Method		Uterature (Year of Publicati on)	Modal	Total Number of Subjects	Nmber of Subjects in each group			Accuracy/%			Remazks
					NC	AD	MCI	AD/NC	NC/MCI	AD/MCI	
SAE		suk[38] 2014	sMRI+PET +CSF	202	52	51	99	98.8	90.7	83.7	ACC(AD/MCI /NC=73.3%
		suk[39] 2013	sMRI+PET +CSF	202	52	51	99	95.9	85	—	
		Liu[40] 2014	sMRI + PET	311	77	65	169	87.7	76.9	—	
		Liu[41] 2015	sMRI+PET	331	77	85	169	91.4	82.1	—	
		Lip[42] 2014	MRl	202	52	51	99	91.4	77.4	—	
		Li[43] 2015	MRl	843	232	200	411	93.8	83.3	86.3	
		Hossei ni-As[44] 2016	MRl	210	70	70	70	97.6	90.8	95.1	
		Dolph[45] 2017	MRl	504	171	101	232	—	—	—	
DBN/IDBM		Broch T[46] 2013	sMRl	300	150	150	NA	NA	NA	NA	
		Suk[47] 2014	MPI+PET	398	101	93	204	95.4	85.7	NA	
		Andŕes[48] 2016	sMRI+PET	249	68	70	111	90.09	81.63	81.1	
		Ratna[49] 2018	MRl	98	49	49	—	91.76	—	—	
CNN	LeNet5	Sarraf[52] (2016)	fMRI	236	92	144	NA	99.9	NA	NA	OASIS; ACC= 93.18%
	GoogLeN		sMRI	302	91	211	NA	98.8	NA	NA	
	VGG	Ciprian[53] (2016)	sMRl	900	300	300	300	98.33	91.67	93.89	
	3D CNN	Li[54] 2017	MRl	428	199	229	—	88.31	—	—	
	DenseNet	Jyotip[55] 2017	sMRl	100	NA	NA	NA	NA	NA	NA	
	CCNN	Liu M[57] 2018	sMRI + PET	397	100	93	204	93.26	74.34	NA	
	3Dlncepti onCNN	Alexander[58] 2018	sMRI+DTI	531	250	53	228	95.9	95.7	95.8	

Note: NA indicates invalid date that is not predicted; AD/NC, NC/MCI, and AD/MCI indicate the classification accuracy of AD and NC, NC MCI, and AD and MCI.

Fluorodeoxyglucose positron emission tomography (FDG-PET) is a functional molecular imaging modality that has been shown to help understand the anatomy and neural variations of the brain associated with AD. Some recent studies have shown that data using multiple modal fusions produces better and more promising results in AD and MCI predictions. Manhua Liu et al.[57] constructed a new concatenated convolutional neural network (CNNs) for extracting multi-level and multi-modal features in MRI and PET images. First, construct several deep 3D-CNNs on image blocks in different brain regions to obtain more representative advanced features. The upper advanced 2D-CNN is then cascaded, followed by the softmax layer, to integrate the advanced features learned from the multimodality and to generate potential multimodal correlation features for the corresponding image blocks of the classification task. Finally, these learned features are combined by fully connected layers, followed by the softmax layer for AD classification. The proposed method can automatically learn general multi-level and multi-modal features from multiple imaging modalities for classification, which is somewhat robust to scale and rotation changes. Image segmentation and rigid registration are not required when pre-processing brain images. The experimental evaluation was performed on baseline MRI and PET images of 397 subjects. The accuracy of 93.26% was obtained for AD and NC classification, and the classification accuracy of pMCI and NC was also 82.95%. Alexander Khvostikov et al.[58] used the 3D initial convolutional neural network (CNN) to fuse sMRI and DTI modal hippocampal regions of interest. Comparison of data using ADNI datasets with traditional AlexNet-based networks indicates that the proposed 3D Inception-based CNN performs better.

The CNN architecture achieves high accuracy in the classification and prediction of neuroimaging. Compared with unsupervised methods such as SAE, the use of CNN's pre-image processing is less, and the original image data can be directly used. This effectively reduces the artifacts in feature selection.

2 Conclusion

2.1 Analysis of database selection in AD/MCI classification research

The rapid development of deep neural network algorithms can make up for the shortcomings of traditional machine learning algorithms, and also provide a new means for the diagnosis of AD/MCI. It has been widely used in the field of neuroimaging. However, most of the current classification studies on AD/MCI are based on the ADNI database for experimental evaluation. Only a small number of documents use other databases or recruit participants to collect data. This results in a large degree of maneuverability of the training and test data used, which may obscure the objective comparison between the methods due to differences between data sets, feature extraction, feature selection, and verification methods.

First, databases such as ADNI, OASIS, and CAD-Dementia provide a more standardized and uniform data set for the classification of AD/MCI. This makes the controllability of selecting the training dataset and the verification data set when performing algorithm verification is large. Therefore, the data used by different research teams to conduct experiments is often a subset of the database, and there are very few documents using the same data set. At the same time, because different subject groups have differences in the selection and prediction or classification accuracy of the experimental objects, even if the same deep neural network architecture is adopted, different classification results will be generated on different data sets. Second, even if the data sets selected in the literature are the same, the selected subjects are the same. If the data distribution and evaluation methods used to establish the model, training, and testing are different, the results of each model cannot be directly compared. Third, because different studies have different characteristics for the representative characteristics of AD/MCI, the results are incomparable. But CNN clearly solves this problem because CNN does not require expert knowledge to define the representative characteristics of AD or MCI. There are few pre-processing of images, and 2D or 3D images can be directly used as input, which effectively reduces the human factors in feature selection.

2.2 Analysis of modal selection of neuroimaging data in AD/MCI classification study

The neuroimaging modalities currently used in the study of AD/MCI diagnosis include structural magnetic resonance imaging (sMRI), functional magnetic resonance imaging (fMRI), positron emission tomography (PET), and diffusion tensor imaging (DTI). However, the most used image modality is structural magnetic resonance imaging. In the survey, it was found that in the study of AD/MCI classification based on deep neural network, many studies not only applied neuroimaging data of different modalities. Some studies have also explored the fusion of two or more modal neuroimaging data in order to obtain better classification results. Most of the literature uses unsupervised deep neural network algorithms (such as SAE, DBN, and DBM) to fuse multimodal neuroimaging data. In these literatures using multimodal image data fusion, most of them are fusions of two data modalities, such as sMRI+fMRI, sMRI+PET or fMRI+PET. However, no scholars have used other modal fusions or three or more modal fusions. At the same time, most convolutional neural network algorithms are based on single modal data, so latecomers can supplement the application of convolutional neural networks in multimodal neuroimaging data fusion.

2.3 Analysis of the presence or absence of image preprocessing in AD/MCI classification studies

Before the MRI image is put into practical use, a series of standardized pretreatment processes, such as post-joining and correction, skull exfoliation, cerebellar clearance, and gray matter separation, are required. These standardized pre-processing processes require special tools such as SPM8, MIPAV, Freesufer, and FSL. It usually takes a lot of time to perform pre-processing with these tools, which is not the result we want. Therefore, Ehsan Hosseini-Asl et al.[44] proposed a classification model based on 3D extended convolution autoencoder (3D-CAE) and migratable features, which overcomes the limitations of brain sMRI feature extraction. First, the MRI data was standardized and preprocessed in the CAD-dementia data set, and then the 3D-CAE was pre-trained with CAD-dementia as the source domain. It was then migrated to the target domain ADNI data set to fine tune the pre-trained 3D-CAE network without pre-processing including data from the skull in the ADNI. The classification performance was measured by ten-fold cross-validation and compared with the prior art model to prove the excellent performance of the proposed 3D-CNN. Deep neural networks do not require pre-definition of features to analyze complex structural features within the problem data. The feature extracted from the preprocessed neuroimaging data is used to construct a deep neural network, which may accelerate the convergence speed of model training, reduce the need for data training, and improve the performance of the model. However, the preprocessing steps for neuroimaging data are cumbersome, and the use of raw data as input also yields good results. Therefore, whether to select the original data or the pre-processed data as input is worth exploring for deep neural network training.

2.4 Analysis of transfer iearning in AD or MCI classification research

Deep neural network models contain millions of parameters and can take weeks or even months to fully train a model. Transfer learning is a method of migrating knowledge learned in one domain to another domain to assist in the completion of tasks. Transfer learning can reduce the work of tuning and make the loss function converge as quickly as possible. However, studies have shown that[59][60] the transitivity of Transfer learning depends on the" distance", which is the difference between the two data sets to be migrated. Although natural images and medical images vary widely, recent studies have shown that[61] Transfer learning between natural images and medical images is possible. Therefore, the combination of Transfer learning and deep neural network is applied in medical image processing, and the performance obtained needs further research.

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深度神经网络在阿尔兹海默病预测中的应用分析

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摘要：综述了深度神经网络方法在阿尔兹海默病分类和预测中的应用. 首先，描述了深度神经网络方法在阿尔兹海默病分类和预测中的优势. 其次，介绍了深度神经网络方法在阿尔兹海默病分类和预测中的具体应用，重点介绍了文献中使用的深度神经网络模型、数据类型、研究人群和特征类型等，并比较它们在AD/MCI 分类中的表现. 最后，预测了该领域未来的发展趋势和挑战.

关键词：阿尔兹海默病；卷积神经网络；深度置信网络；神经影像

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