A Review on Multimodal Brain Image Fusion using Deep Learning for Alzheimer's disease

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Abstract : Alzheimer's disease (AD) may be a progressive encephalopathy and therefore the commonest explanation for dementia in later life. It causes cognitive deterioration, eventually leading to inability to hold out activities of lifestyle. Alzheimer's disease is an incurable, progressive neurological encephalopathy. Early diagnosis of Alzheimer's disease can help with proper treatment and stop brain tissue damage. Several statistical and machine learning models are exploited by researchers for Alzheimer's disease diagnosis. Detection of Alzheimer's disease is exacting thanks to the similarity in Alzheimer's disease resonance Imaging (MRI) data and standard healthy MRI data of older people. Recently, advanced deep learning techniques have successfully demonstrated human-level performance in numerous fields including medical image analysis. convolutional neural network for Alzheimer's disease diagnosis using brain MRI data analysis. Experiments on the Alzheimer's Disease specify that the proposed image fusion method achieves better overall performance than unimodal and feature fusion methods, and that it performance state-of-the-art methods for AD diagnosis.

IndexTerms **-Alzheimer, Convolutional Neural Network, Deep learning, Image Fusion, Magnetic resonance imaging.**

I. INTRODUCTION

Alzheimer's disease (AD) is an irreversible brain disorder that severely damages human thinking and memory. Early diagnosis plays a crucial part within the prevention and treatment of AD. Neuro imaging-based computer-aided diagnosis (CAD) has shown that deep learning methods using multimodal images are beneficial to guide AD detection. In recent years, many methods supported multimodal feature learning are proposed to extract and fuse latent representation information from different neuro imaging modalities including resonance imaging (MRI) and 18-fluorodeoxyglucose positron emission tomography. However, these methods lack the interpretability required to obviously explain the precise meaning of the extracted information. to form the multimodal fusion process more persuasive, we propose a picture fusion method to assist AD diagnosis. Specifically, we fuse the grey matter (GM) tissue area of brain MRI and FDG-PET images by registration and mask coding to get a replacement fused modality called "GM-PET." The resulting single composite image emphasizes the GM area that's critical for AD diagnosis, while retaining both the contour and metabolic characteristics of the subject's brain tissue. additionally, the three-dimensional simple convolutional neural network and 3D Multi-Scale CNN is the effectiveness image fusion method in binary classification and multi-classification tasks.

II. ALZHEIMERS DIEASE

Aversen et al. [1] used dimensionality reduction methods, Brosch et al. [3] developed a deep belief network model, Gupta et al. [4] developed a sparse autoencoder model and Payan et al. combined sparse auto encoders and 3D CNN model for AD detection and classification. Earlier we developed a really deep convolutional neural. Alzheimer's disease features a certain progressive pattern of brain tissue damage. It shrinks the hippocampus and cerebral mantle of the brain and enlarges the ventricles. Brain MRI images presenting different AD stages. Some remarkable research works are finished automated Alzheimer's disease diagnosis. Aversen et al. used dimensionality education methods, Brosch et al. developed a deep belief network model, Gupta et al. developed a sparse auto encoder model and Payan et al. combined sparse auto encoders and 3D CNN model for AD detection and classification. Earlier we developed a really deep convolutional neural network using transfer learning for AD diagnosis. Here, we improved the previous model and developed a deep convolutional neural network and demonstrated superior performance on the OASIS dataset.

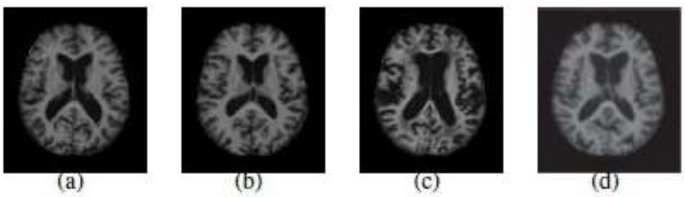

Fig. 1 Different AD stages a) Non demented b) Very Mild Dementia c) Mild Dementia d) Moderate Dementia

III. DEEP LEARNING FOR MULTIMODAL IMAGE FUSION

Deep learning may be a new field of medical image fusion research in recent years. Convolutional neural network (CNN) may be a typical deep learning model Compared with medical image fusion, deep learning is widely utilized in the segmentation and registration of medical images. The medical image fusion methods supported spatial domain and transform domain have the defects of activity level measurement and fusion rules, which require artificial design, and therefore the correlation between them is extremely small. so as to beat the above problems. The U-Net network model is widely utilized in medical image segmentation. From 2D to 3D , its research technology has been relatively mature and has achieved good leads to the sector of medical image segmentation, but medical image fusion may be a new field. There are many fusions of imaging methods in medical image fusion, like MRI and PET, MRI and CT, MRI and SPECT, CT and PET, CT and SPECT, SPECT and PET, and MRI-T1 and MRI-T2. alternative ways of integration keep their own characteristics, like MRI/PET fusion images which are important for detecting liver metastasis, Alzheimer's disease, and brain tumour diagnosis; MRI/SPECT fusion images are helpful for the localization of lesions and vertebral bone metastasis in tinnitus patients; CT/PET fusion image energy improves the diagnosis of lung cancer; SPECT/PET for abdominal research; and ultrasound/MRI for vascular blood flow diagnosis.

3.1 Multimodal Fusion

MRI, also referred to as magnetic resonance Imaging, provides information[5] on the soft tissue structure of the brain without functional information. The density of protons within the systema nervosum , fat, soft tissue, and articular cartilage lesions is large, therefore the image is especially clear and doesn't produce artifacts. it's a high spatial resolution and no radiation damage to the physical body , and therefore the advantage of rich information makes it a crucial position in clinical diagnosis. The density of protons within the bone is extremely low, therefore the bone image of MRI isn't clear. The CT image is named computerized tomography imaging. The X-ray is employed to scan the physical body . The high-density absorption rate of bone tissue relative to soft tissue makes the bone tissue of the CT image particularly clear. The low permeability of X-rays in soft tissue results in low absorption rate, so CT images show less cartilage information, which represents anatomical information. SPECT is named Single-Photon Emission computerized tomography , which may be a functional image that displays the metabolism of human tissues and organs and therefore the blood flow of arteries and veins. It provides good and malignant information of tumors and is widely utilized in the diagnosis of varied tumor diseases. However, the resolution of SPECT[13] is low and therefore the positioning ability is poor. The PET image is named Positron Emission Tomography, which reveals truth information of blood flow and may accurately identify the situation of the patient's lesion. Its principle is using positrons to get photons in collision with electrons within the tissue. the aim of PET is to detect the amount of photons, showing a color image of brain function information, suitable for tumor detection; its sensitivity is high, but it's difficult to get accurate brain structure position information; soft tissue and bone boundary resolution is lacking, therefore the spatial resolution is extremely low and therefore the spatial distortion is very probable.

3.2 MRI and PET Fusion

MRI may be a gray image while PET may be a color image, which is definitely distorted within the fusion processing. In most fusion algorithms, the IHS model is employed to decompose the intensity components of PET image [8], and BEMD, Log-Gabor transform, and other algorithms are combined to process these components, so on preserve more color of PET image. Yin et al. [26] proposed an MRI and PET image fusion algorithm supported NSST and S_PCNN, which converts the PET image into YIQ component, then used NSST to decompose MRI and therefore the Y component of PET into low-frequency and high-frequency subbands. The implified PCNN model was wont to process high-frequency coefficients; the fused image has good effect, small color distortion, and rich structural information. Wang et al. [17] proposed a preparation method supported discrete wavelet transform for preprocessing of MRI and PET image fusion, which solved the matter of quality degradation and unreadability of input images, and therefore the fusion accuracy was as high as 90%-95%. Chaitanya et al. [67] proposed a replacement fusion method by combining shearlet transformation and discrete cosine transform. Arash and Javad [68] first applied adaptive filters to the fusion of MRI-PET images, using spatial and spectral difference criteria to optimize filter coefficients. There are other MRI/PET fusion methods. MRI/PET images are often involved within the clinical diagnosis of Alzheimer's disease, and therefore the fusion of MRI and PET images is what's needed to satisfy the diagnosis.

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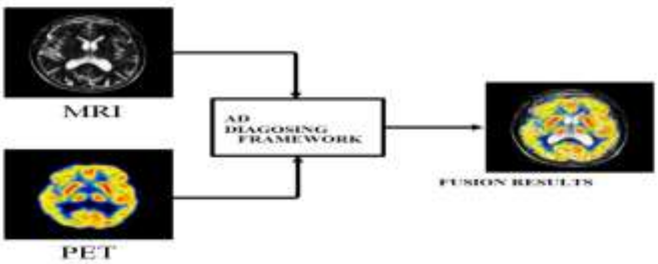

Fig. 2:-AD diagnosing framework

3.3 MRI and CT Fusion

The combination of MRI and CT combines the benefits of clear bone information in CT images and therefore the clear soft tissue of MRI images to catch up on the shortage of data during a single imaging. Na et al. [12] proposed a MRI and CT fusion algorithm supported guided filtering (GF). The fused image not only preserves the sting information of the source image but also extracts the feature information, which solves the matter of edge degree and clarity. In [13], the Frei-Chen operator fusion algorithm supported NSST domain is proposed. The visual analysis of fusion results has obvious improvement in contrast and structural similarity. Quantitative evaluation is additionally an extra improvement of existing methods.

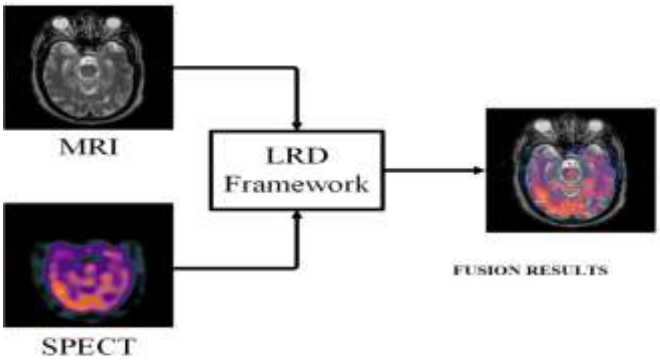

Fig. 3: LRD Framework

3.4 Convolutional Neural Network (CNN)

CNN may be a multistage feedforward artificial neural network with trainable supervised learning. The convolution operation is multidimensional. during a convolutional network, the primary parameter is typically called an input, and therefore the second parameter is named a kernel function, and therefore the output is named a feature map. Sparse representations (also referred to as sparse weights), parameter sharing, and isomorphic representations are three important architectural ideas of CNN. Traditional neural networks use matrix operation to affect connection relationships. An output unit is related to each input unit, which inevitably requires tons of storage. However, the character of the sparse representation of the convolutional network and therefore the neurons are only connected to many neurons[11] adjacent to the previous stage, and therefore the local convolution operation is performed, which reduces the storage requirements and improves the computational efficiency. CNN's parameter sharing abandons the non uniqueness of weights in traditional networks. The weights within the CNN stage are constant, which is best than others in storage requirements. Traditional automatic encoders are fully connected. Vector output and source image aren't necessarily aligned in space, while U-Net uses local connection structure. Vector output and source image are aligned in space, therefore the visual effect of fusion image is best . U-Net may be a full-convolution network [16], which consists of contraction path and expansion path. In-depth learning training needs an outsized number of samples, while U-Net is improved supported full convolution neural network, and may train alittle number of samples using data enhancement. This advantage just caters to the shortcoming of alittle sample size of medical image data. The most promising measurements seem to be resonance imaging (MRI) for AD vs control (CTL) discrimination with 97.95% accuracy, while electroencephalogram (EEG) shows the simplest results for mild cognitive impairment (MCI) vs CTL (98.88%) and MCI AD distinction (95.05%). To validate the effectiveness of the proposed Alzheimer's disease diagnosis model, we've developed two baselines deep CNN, Inception-v4 [12] and ResNet [5] and modified their architecture to classify 3D brain MRI data. we've considered four metrics for quantitative evaluation and Comparison, including accuracy, precision, recall, and f1–score. The OASIS dataset [9] has 416 data samples. Divided the dataset into training and test dataset in 4:1 proportion. A validation dataset was prepared using 20% data from the training dataset.

TABLE I:-PERFORMANCE ANALYSIS

Class	Precision	Recall	F1–Score	Support
Non-Demented	0.99	0.99	0.99	6
Very Mild	0.75	0.50	0.60	6
Mild	0.62	0.71	0.67	7
Moderate	0.33	0.50	0.40	2

V.CONCLUSION

The GM-PET modality contains both brain anatomic and metabolic information and eliminates image noise subtly in order that the observer can easily specialise in the key characteristics. To further evaluate the applicability of the proposed image fusion method, 3D Grad-CAM technology was wont to visualize the world of interest of the CNN in each modality, showing that both the structural and functional characteristics of brain scans were included within the GM-PET modality. A series of evaluations supported the 3D Simple CNN and 3D Multi-Scale CNN confirmed the prevalence of the proposed image fusion method. In terms of experimental performance, our proposed image fusion method not only overwhelmingly surpassed the unimodal methods but also outperformed the feature fusion method. Besides, the image fusion method showed better performance than other competing multimodal learning methods described within the literature. Therefore, this image fusion method is an intuitive and effective approach for fusing multimodal information in AD classification tasks

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