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Intelligent diagnosis of Alzheimer's disease based on deep learning algorithm

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Abstract

Alzheimer's disease is an irreversible neurodegenerative disease of the brain, with a long incubation period, and clinical symptoms slowly deteriorate with the growth of time, clinical signs include memory loss, memory loss, language degradation, and irreversible. At present, the main clinical diagnosis basis is to observe the patient's nuclear magnetic image, so this paper proposes to identify the medical image of the patient with Alzheimer's disease based on the good performance and characteristics of the deep learning algorithm, which has far-reaching significance for the intelligent diagnosis of Alzheimer's disease. This paper obtains data from the ADNI database and uses a deep learning algorithm to identify and classify patients' nuclear magnetic images. The main work completed is as follows: (1) Data processing. A large number of medical images of patients with different degrees were collected in the ADNI database. First, the image format was converted to convert high-dimensional image data into low-dimensional photos, and then irrelevant images were manually screened. Finally, in order to prevent the phenomenon of overfitting of the model, image enhancement was performed. (2) It specifically introduces the structure and principle of deep learning algorithms and the current popular network model architecture. In order to better recognise the NMR images of Alzheimer's disease, this paper proposed an intelligent diagnosis of Alzheimer's disease based on a deep learning algorithm. Three network models, ResNet, EfficientNet, and ViT, were used to extract and classify the features of the NMR images to achieve the final classification effect. (3) This paper designs an algorithm that combines the unsupervised feature learning algorithm IPCA with the convolutional neural network algorithm. First, the unsupervised feature learning algorithm is used to preprocess the original high-dimensional data, and the features of the high-dimensional data are mapped to the low-dimensional data to achieve feature extraction and data dimensionalisation reduction. Then, the output dimensionalisation data is used as the input of the convolutional neural network algorithm, and the processed medical image data is further calculated by combining the advantages of the two algorithms. It has been verified that the improved neural network algorithm has improved the classification accuracy of Alzheimer's disease.

Keywords

Deep learning; Alzheimer's disease; Unsupervised feature learning; Image recognition.

1. Introduction

Alzheimer's disease is a degenerative disease of the nervous system, and the onset is not easy to detect; the incubation period is long. The clinical manifestations include memory impairment, aphasia, apraxia, agnosia, damage to visuospatial skills, and decreased executive ability, which are irreversible. Although some studies have shown that genetics, immunity, and neurotransmitters are the main factors causing Alzheimer's disease, there are no scientific and technological means to cure the disease completely. According to the 2020 population survey results, there are about 15 million dementia patients among the elderly over 60 years old in China, of which 10 million are Alzheimer's patients. In 2015, the annual diagnosis and treatment cost of Alzheimer's patients in China was about 170 billion US dollars. With the development of the economy and science and technology, it is expected to be as high as about $19,000 in 2050. In 2019, about 1.6 million people died from Alzheimer's disease worldwide, of which more than 320,000 died from the disease in China, accounting for about 20% of the world's total.

At present, the medical means for the diagnosis of Alzheimer's disease include neuroimaging examination, neuropsychological assessment, body fluid markers, gene detection, etc. Neuroimaging study includes nuclear magnetic resonance imaging (MRI), computed tomography (CT), and positron emission computed tomography (PET). Neuropsychological assessment is usually conducted by professionals in accordance with the requirements of patients in the form of scale assessment, mainly including cognitive assessment and non-cognitive assessment. The diagnostic sensitivity of body fluid markers was good, which primarily included cerebrospinal fluid, blood, and urine. Genetic testing is not applicable to all clinical patients; the purpose and method of gene testing for Alzheimer's disease patients are still immature, and it is expected that the process of genetic testing will be more reasonable and standardised and can be applied to many patients. Nowadays, MRI imaging in neuroimaging examination is one of the main bases for doctors' diagnosis methods. After a patient has undergone an MRI examination, clinicians need a certain time and experience to select sections with diseased parts from many MRI sections. This selection process consumes a lot of manpower and material resources and requires clinicians' rich diagnostic experience. At the same time, it will increase the time for patients to wait for MRI reports. To improve MRI images, clinicians can only manually screen lesion sections and reduce the time for patients to be diagnosed. Therefore, this paper proposes to use deep learning algorithms to intelligently identify and classify MRI images of patients with Alzheimer's disease. Deep learning has great advantages in feature extraction of high-dimensional image data, which can assist doctors and patients in diagnosing their conditions to varying degrees to achieve early prevention, early detection, and early treatment.

2. Research method

In this paper, medical image data of patients with Alzheimer's disease in different periods were extracted from the ADNI database, including 23,402 MRI image data. Then, the extracted data was pre-processed, including the original format image data, and processed into a PNG format image. The image of this format is processed into two forms: one is a single-section slice, and the other is a multi-section slice combination. The data enhancement operations of the two different forms of images include image flipping, image rotation, image scaling, image brightness transformation, replication affine transformation, image brightness, and contrast change, which improves the robustness and generalization ability of the model. At the same time, the phenomenon of data overfitting can be avoided. This experiment proposes to combine the unsupervised algorithm IPCA and deep learning network to calculate the medical image of Alzheimer's disease. The specific steps of this experiment are divided into five parts: the first part is to calculate the single-layer slice data by using the deep learning network, the second part is to calculate the multi-section slice data by using the deep learning network. The third part is the calculation of raw data by IPCA algorithm, the fourth part is the calculation of single slice data by combining IPCA algorithm and deep learning network, and the fifth part is the calculation of multi-section slice data by combining IPCA algorithm and deep learning network.

The evaluation indexes of each experimental piece are calculated. It proves that the proposed research method can assist clinicians in making intelligent diagnosis of Alzheimer's disease patients.

3. Data and pre-processing

3.1. Data profile

Data from ADNI (Alzheimer's Disease Neuroimaging Initiative) open database. Established in 2003 by the National Institutes of Health and the National Graduate Students of Biomedical Imaging and Bioengineering, the database is a longitudinal multi-centre study that includes clinical, genetic, and imaging and is a large clinical and imaging database. For more than a decade, the ADNI database has collected many medical images of Alzheimer's patients in different periods, which not only facilitates the early detection of patients and the tracking of Alzheimer's disease but also provides a large amount of data for the global scientific researchers engaged in this research, which has contributed to this research. A total of 23402 MRI image data were selected from ADNI-1, ADNI-2, and ADNI-GO after screening. Among them, there were 4,018 cases of Alzheimer's Disease Group (AD), Mild Cognitive Impairment (Mild Cognitive Impairment), and a prior stage of Alzheimer's disease. MCI) 10204, Normal Control (NC) 9180.

3.2. Data processing

The data collected from ADNI in this paper are medical images in nii format. Since the data in nii format is computation-intensive in processing, it is not applicable to the actual situation. Therefore, according to the requirements, the data in nii format is processed into a form combining single-layer slices and multi-section slices.

To improve the robustness and generalization ability of the model and avoid data overfitting, data enhancement processing is carried out on the single-layer slice data. The data enhancement methods include image flipping, image rotation, image scaling, image brightness transformation, image affine transformation, image brightness and contrast change. The methods of data enhancement in this study are as follows:

(1) The number and diversity of samples in the data set can be enhanced by flipping the image, that is, by symmetric transformation of left and right or up and down. Taking single-layer slice data as an example, the same slice can be flipped horizontally or vertically to get a new piece, thereby increasing the number of samples in the data set. This kind of symmetric transformation can make the neural network model better capture the features of different directions and angles in the data set, thus improving the performance and robustness of the model. Therefore, it is very common and effective to use symmetric transformation to enhance data in model training.

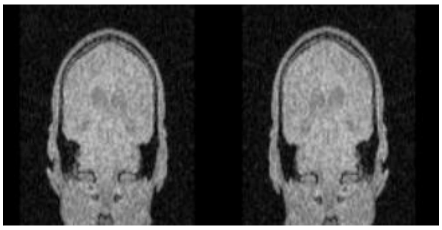

Figure 1: Original image and flipped single-layer slice image

Where i, j, and c represent integers, and where the tensor P represents the original picture, which is a tensor with three dimensions corresponding to the height, width, and number of channels of the image. To enhance the diversity of the data set, a symmetric transformation can be performed to generate a new picture tensor. Specifically, the original picture can be flipped horizontally or vertically to get a new tensor, usually expressed as Pa, where H represents the

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height, and W represents the width in the view. The formula of image symmetry transformation is:

$$\begin{cases} P_a[i\, j\, c] = P\,[i\,, W - j,\, c] \\ 1 \leq i \leq H \\ 1 \leq j \leq W \\ 1 \leq c \leq 3 \end{cases}$$

(2) Through image rotation, the data was enhanced; the image was rotated 45 degrees and 60 degrees clockwise and counter clockwise, and the original number of slices was expanded to 5. Take single-layer slice data as an example, as shown in the figure.

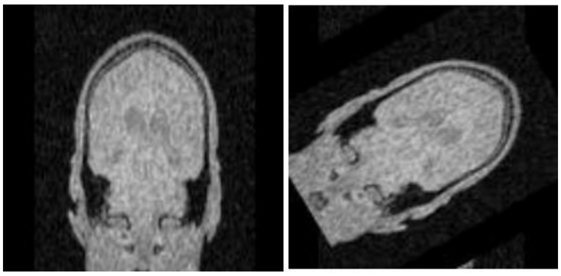

Figure 2: The original image and the single layer slice after rotation

Through image scaling, the data is enhanced, and the idea is reduced to 0.5 times the original size, as shown in Figure 3:

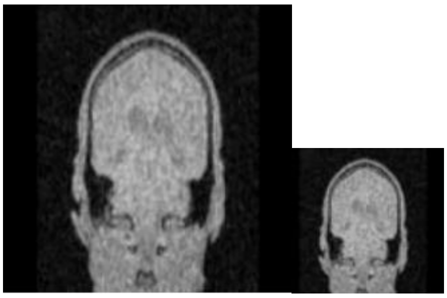

Figure 3:Original image and reduced single-layer slice picture

The data is enhanced by changing the brightness of the image, as shown in Figure 4.

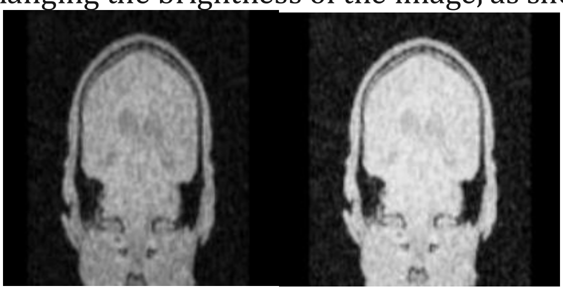

Figure 4: Single-layer slice picture after the original image and brightness change

Enhance the data by means of image affine changes, and set the rotation Angle, scaling ratio, and miscutting Angle of the image, as shown in Figure 5:

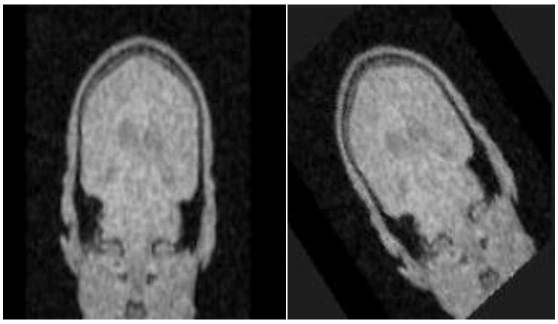

Figure 5: Original and affine single-layer slice images

The data is enhanced by changing the brightness and contrast of the image, as shown in Figure 6:

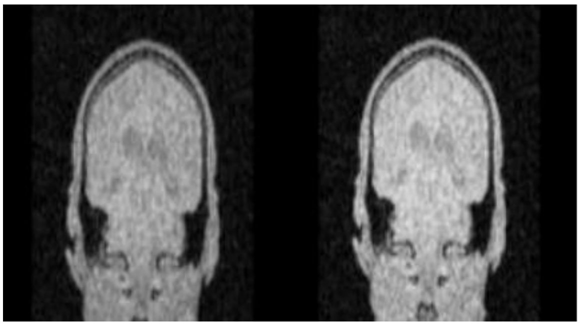

Figure 6:The original image and the single-layer slice image with changed brightness and contrast

In this paper, data enhancement operations are carried out on single-layer slice data and multi-section slice data respectively. Through data enhancement, the robustness and generalization ability of the model are improved, and the effect of data overfitting can be avoided.

4. Application of IPCA algorithm in Alzheimer's disease

This chapter mainly introduces the specific steps of the experiment, which is divided into five parts: the first part is to calculate single-layer slice data using a deep learning network; the second part is to calculate multi-section slice data using a deep learning network; the third part is to calculate raw data using IPCA algorithm; the fourth part is to calculate single-slice data combining IPCA algorithm and deep learning network. The fifth part is the combination of the IPCA algorithm and deep learning network to calculate multi-section slice data.

4.1. Single slice data experimental method

First, the original data collected from ADNI is processed into single-layer slices. To improve the robustness and generalization ability of the model and avoid data overfitting, data enhancement is performed on the single-layer slice data. The methods of data enhancement include image inversion, image rotation, image scaling, image brightness transformation, image distortion, image affine transformation, image brightness and contrast change, and the slice data after data enhancement is passed into the deep learning network layer respectively. Deep learning network models, including ResNet models, Efficient Net models, and Vit models, learn from the processed data and then feed it into the fully connected layer to output classification results. The specific structure is shown in Figure 7 below, from ADNI to sectional slice combination to data enhancement to enhanced slice data to deep learning network to fully connected layer to output AD\MCI\NC.

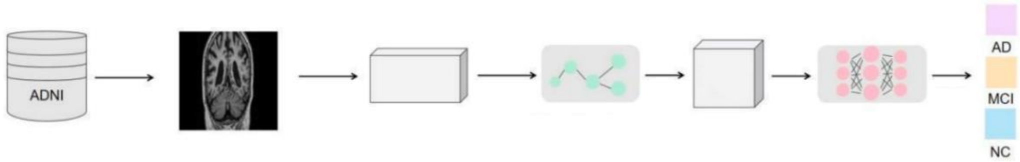

Figure 7: Structure of single-slice data experimental method

4.2. Experimental method of multi-section slice data

Firstly, the original data collected from ADNI is processed into multi-section section data, and the combined sections of different dimensions are analysed. The sections extracted from different sections of the nuclear magnetic image are the coronal plane (upper left), sagittal plane (upper right), and cross-section (lower left), and then combined. This processing method has been specifically introduced in Section 3.2. Data enhancement was performed on the multi-section slice data. After data enhancement, the slice data was passed to the deep learning network layer respectively. The deep learning network models included the ResNet model, Efficient Net model, and Vit model, and then to the full connection layer to output the classification results. The specific structure is shown in Figure 4.2 below:

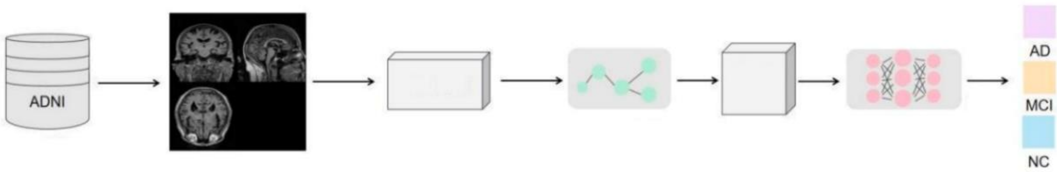

Figure 8: Multi-slice data experimental method structure diagram

4.3. Experimental method of raw data calculation by IPCA algorithm

In the experiment, it was found that the single-layer slice data and the cross-section slice combination data were missing some features of 3D data, so the IPCA algorithm was proposed. Firstly, the IPCA algorithm is used to calculate the original data collected from ADNI, which can not only ensure less computation but also retain many original data features. The calculated data was enhanced, and the processed data was transferred to the deep learning network layer respectively. Deep learning network models including the ResNet model, Efficient Net model, and Vit model were then transferred to the full connection layer to output classification results. The specific structure is shown in Figure 9 below:

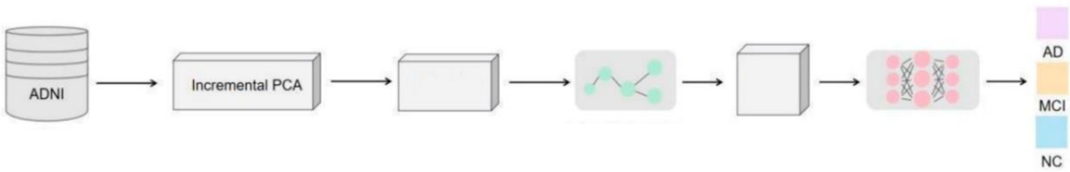

Figure 9: Structure of experimental method for multi-section slice data

4.4. IPCA algorithm combined with deep learning to calculate single-layer slice data experimental method

After calculation, it is found that the results of calculation and classification are not good when the IPCA algorithm is used alone to process data. Therefore, it is proposed to combine the data processed by the IPCA algorithm with multi-section slice data. This processing method has been specifically introduced in Section 3.2, and then the deep learning model is used to achieve better classification results. The IPCA algorithm processes the data results and combines the single-layer slice data. The data collected from ADNI is processed by single-layer slice data, and the IPCA algorithm is used for data processing. The two data processing methods are combined, and data enhancement is carried out. The processed data is transferred to the deep learning network layer respectively. Deep learning network models including the ResNet model, Efficient Net model and Vit model are then passed into the full connection layer to output classification results.

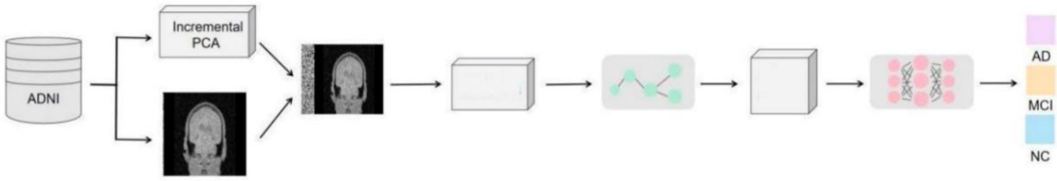

Figure 10: Structure of IPCA algorithm combined with deep learning to calculate single slice data

4.5. IPCA algorithm combined with deep learning to calculate multi-section slice data experimental method.

To compare, the IPCA algorithm is proposed to combine the data processing results with the sectional slice combination data to calculate the classification results. The data collected from ADNI is processed by multi-layer slicing data respectively, and the IPCA algorithm is used to combine the multi-section slicing data. The multi-section slicing data processing method has been specifically introduced in Section 3.2. The two data processing results are combined, data enhancement is carried out, and the processed data is transferred to the deep learning network layer respectively. Deep learning network models including the ResNet model, Efficient Net model and ViT model are then passed into the full connection layer to output classification results. The specific structure is shown in Figure 11 below:

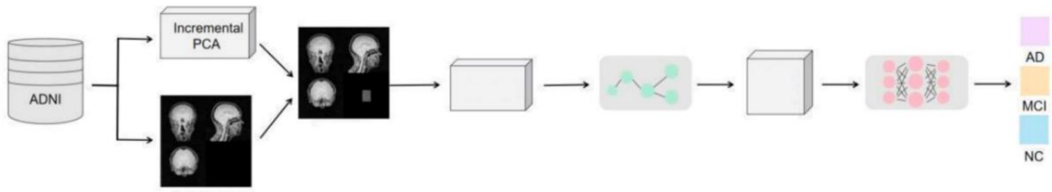

Figure 11: IPCA algorithm combined with deep learning to calculate multi-section slice data experimental method structure

5. Experimental results and analysis

In this paper, data collected from the ADNI database was used to verify the effectiveness of the proposed algorithm. In comparison experiments, different data processing methods were used, combined with IPCA algorithm and three deep learning network models, ResNet model, Efficient Net model, and Vit model, for calculation. In this article, we have chosen an optimizer called Adam, which is one of the most used optimizers to help us update parameters more efficiently when training models. To evaluate the performance of our model, we used two metrics, accuracy, and loss. The accuracy rate reflects how correctly our model is classified on the test data set, while the loss value represents the size of the model's error during training. For the experiment, the operating system we used was Linux with 128GB of memory, and the main development environment was python3.6.7. With these tools and environments, we were able to train and evaluate our models more efficiently, using a deep learning network running on a 16GB Tesla V100 GPU.

5.1. Experimental results of single-slice data

The original data was processed into a single layer slice, and deep learning network models (ResNet model, Efficient Net model, Vit model) were used to train the processed medical image data, and the accuracy and loss images of the single slice medical image data in each network training set were drawn, as shown in Figure 12:

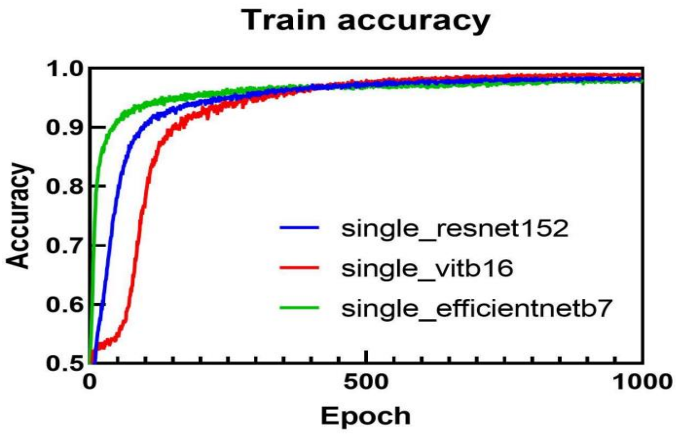

Figure 12: Accuracy of training set of single slice data experimental method

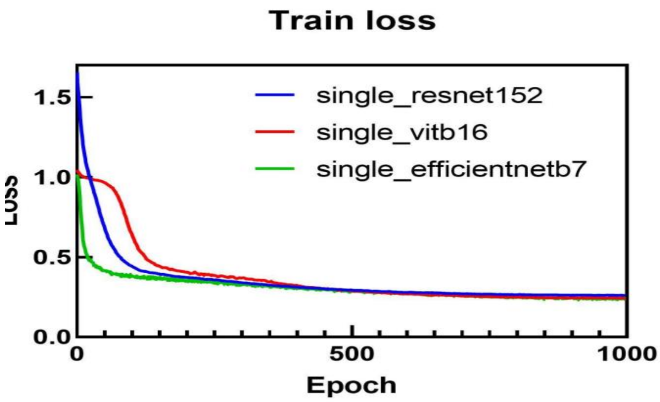

Figure 13: loss value of the training set of single-slice data experimental method

Figure 12 and Figure 13 show that the Efficient model has the best training effect and the highest accuracy at the beginning, followed by ResNet model and ViT model, and the model effect changes after reaching a certain depth. When the Epoch value of the Efficient model is 50, the loss value gradually flattens. The experimental results of the first part are shown in Table 1 below:

Table 1: The first part is the index table of experimental results

Model	Predicted Class	Precision	Recall	Fl-score	Accuracy
single_resnet152	AD	0.9585	0.8098	0.8779	92.13%
	NC	0.9038	0.9231	0.9160	
	MCI	0.9015	0.9314	0.9175	
single_vitbl6	AD	0.8744	0.7146	0.7863	85.12%
	NC	0.8451	0.8723	0.8520	
	MCI	0.8582	0.8940	0.8920	
single_efficientnetb7	AD	0.8322	0.6253	0.6271	82.31%
	NC	0.8214	0.8283	0.8291	
	MCI	0.8159	0.8812	0.8819	

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Results show that the first part of the ResNet network model works best, accuracy is 92.13%, the Vit model accuracy rate was 85.92%, and the Efficient Net model accuracy is 82.31%.

5.2. Experimental results of multi-section slice data

The original data were processed into multi-section slices, and deep learning network models (ResNet model, Efficient Net model, Vit model) were used to train the processed medical image data and the accuracy and loss images of the multi-section medical image data in each network training set were drawn. See Figures 14 and 15 below:

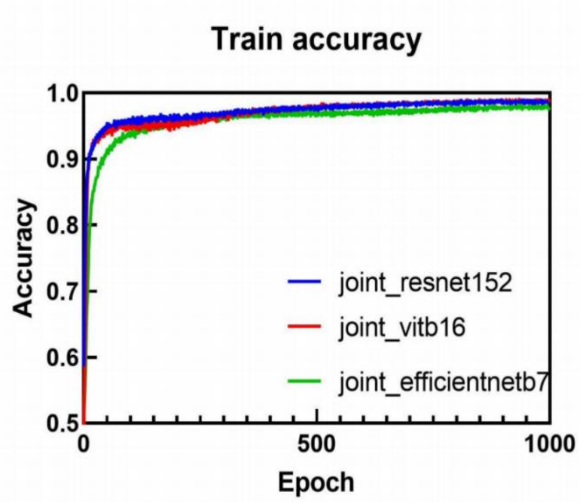

Figure 14: Accuracy of training set of multi-section slice data experimental method

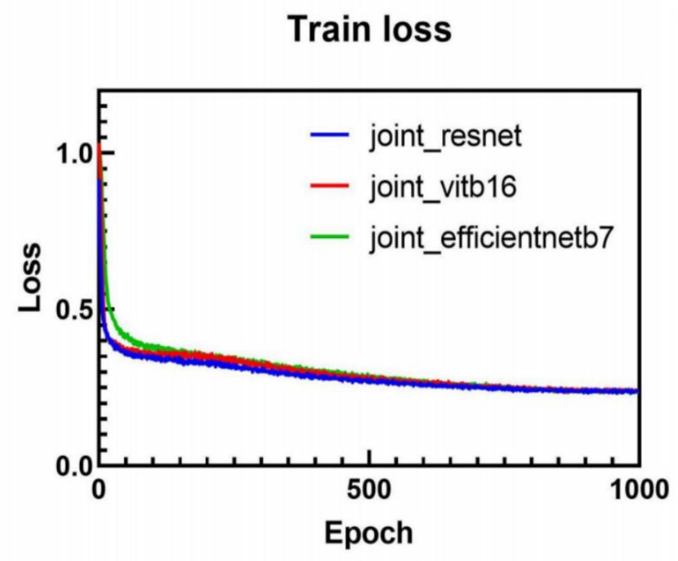

Figure 15: loss value of the training set of multi-section slice data experimental method

Figure 14 and Figure 15 show that the ResNet model has the best training effect and the highest accuracy, followed by the ViT model and Efficient model. After the first few iterations, the three models rapidly decline, and the loss value gradually flattens out. The loss value of the ResNet model began to decline first. The second part of the experimental results are shown in Table 2 below:

Table 2: The second part of the experimental results index table

Model	Predicted Class	Precision	Recall	Fl-score	Accuracy
single_resnet152	AD	0.9393	0.7945	0.8608	91.87%
	NC	0.9101	0.9351	0.9224	
	MCI	0.9068	0.9358	0.9211	

single_vitbl6	AD	0.8441	0.7062	0.7680	84.81%
	NC	0.8537	0.8583	0.8560	
	MCI	0.8467	0.8936	0.8695	
single_efficientnetb7	AD	0.8280	0.6123	0.6904	82.00%
	NC	0.8290	0.8217	0.8229	
	MCI	0.8031	0.8812	0.8442	

The second ResNet network model showed the best results, with an accuracy of 91.87%, the Vit model with an accuracy of 84.81%, and the EfficientNet model with an accuracy of 82.00%.

5.3. IPCA algorithm combined with deep learning to calculate the experimental results of multi-section slice data.

IPCA algorithm to handle data results and cross-section slice data, using deep learning network model (ResNet model, EfficientNet model, Vit model) for processing the data for training, The accuracy and loss images of the training set processed by IPCA algorithm and the combined data of multi-section slices in each network are drawn, as shown in FIG. 16 and FIG. 17 below:

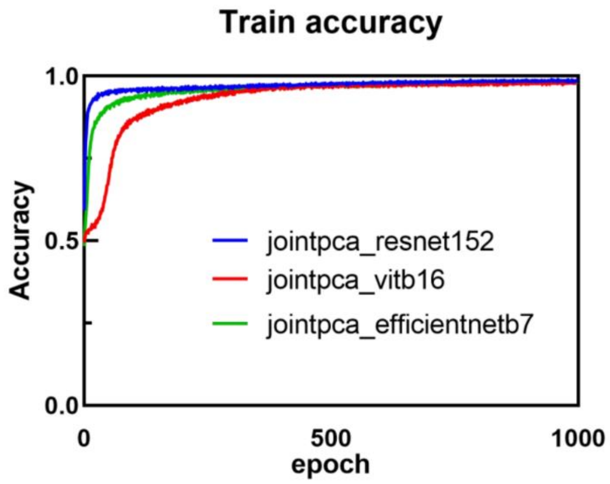

Figure 16: IPCA algorithm combined with deep learning to calculate the accuracy of training set of multi-section slice data experimental method

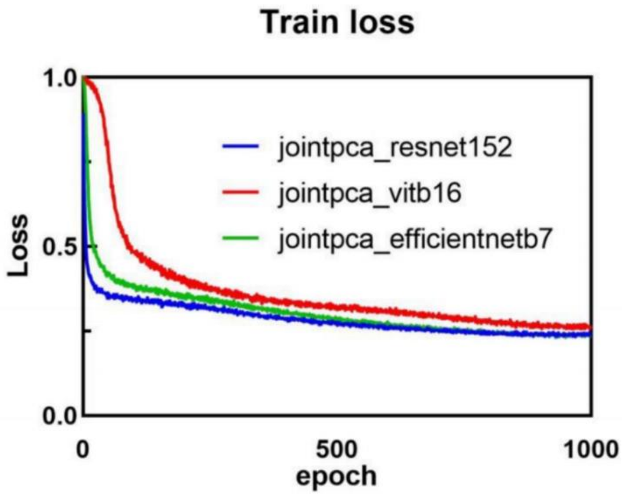

Figure 17: IPCA algorithm combined with deep learning to calculate the loss value of the training set of multi-section slice data experimental method

By figure 16 and figure 17, according to the initial ResNet model training effect is best, with the highest accuracy, followed by the Efficient model and ViT model. The experimental results of the fifth part are shown in Table 3 below:

Table 3: The third part is the index table of experimental results

Model	Predicted Class	Precision	Recall	Fl-score	Accuracy
single_resnet152	AD	0.9382	0.8406	0.8867	92.38%
	NC	0.9100	0.9393	0.9245	
	MCI	0.9234	0.9320	0.9277	
single_vitbl6	AD	0.7869	0.7609	0.7737	83.33%
	NC	0.8455	0.8614	0.8527	
	MCI	0.8674	0.8632	0.8671	
single_efficientnetb7	AD	0.8307	0.6140	0.7061	81.61%
	NC	0.8217	0.8089	0.8153	
	MCI	0.7961	0.8839	0.8377	

The third part, the ResNet network model, had the best results, with an accuracy of 92.39%, the Vit model with an accuracy of 83.33%, and the Efficient Net model with an accuracy of 81.61%.

6. Conclusion

Compared with the results of calculating multi-section slice data using the combination of IPCA and deep learning network, the accuracy of other networks is not significantly improved except for the ResNet network, which increases by 0.52%. Among them, the experimental method with the best classification effect is the method of combining IPCA and deep learning networks to calculate multi-section slices, and the accuracy rate is 92.39%. This study proved that the method of combining the IPCA algorithm and deep learning network to calculate the single section data of the nuclear magnetic image of Alzheimer's disease could ensure a small amount of computation and retain the characteristics of high-dimensional data as much as possible and can improve the accuracy of algorithm classification. Therefore, the method proposed in this experiment has practical significance in the current auxiliary diagnosis of Alzheimer's disease. This paper studies the method of intelligent diagnosis of Alzheimer's disease and proposes a structure based on an IPCA algorithm combined with a deep learning network, which can improve the accuracy of algorithm classification on the premise of ensuring a small amount of computation and retaining high-dimensional data features as much as possible. Therefore, the method proposed in this experiment can be used in the current diagnosis of Alzheimer's disease. It can reduce the calculation time of diagnosis, improve the efficiency and accuracy of diagnosis of the disease, reduce the misdiagnosis rate for patients, and achieve early detection and early treatment, which has great practical significance.

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