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Alzheimer's Disease Diagnosis Based on Supporting Tensor Machine Algorithm and 3D Brain White Matter Images

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Abstract: Alzheimer's disease usually has an incubation period, which is a slow and irreversible process, and is common in mental disorders clinically. Because of the irreversible damage and death of brain cells, the medical community has not yet found an effective method to treat the disease, so early diagnosis and early prediction of Alzheimer's disease are critical. This article aims to study the diagnosis of Alzheimer's disease based on supporting tensor machine algorithms and 3D brain white matter images. This paper proposes a classification method based on the third-level tensor method. The method takes the gray matter gray level of the MRI image as the feature, extracts the gray level of each voxel of the gray matter, and obtains the third-level gray level tensor. Tensor-based independent component analysis is used to obtain the independent components of the third-level grayscale tensor; in order to reduce the feature dimension, the support tensor machine is used to convert the tensor feature into a vector feature, and then the recursive feature elimination method is used to obtain the effective The main characteristics. The experimental results of this paper show that compared with traditional vector space machine learning, the algorithm proposed in this paper will use the original high-order tensor image as input data, which improves the consistency of data structure information by 15%. In addition, it supports the deletion of recursive features and tensor The machine-combined feature selection algorithm effectively eliminates redundant information and selects the best subset, which improves the performance of the classifier by 23%. It can effectively identify patients with AD and MCI.

1. Introduction

Computer-aided diagnosis based on medical images is a major trend in the development of medicine, and its core is to establish an effective classification algorithm. In recent years,

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classification algorithms such as linear discriminant analysis (LDA), independent component analysis (ICA), and support vector machine (SVM) have been effectively used in the diagnosis of Alzheimer's disease. However, these methods first expand the image data that essentially has a 3D tensor structure into vectors, which will not only cause the loss of spatial structure information, but also greatly increase the feature dimension after vectorization, which is likely to cause small sample events and dimensionality disasters.. With the effective expression of tensor data and the development of multi-linear space optimization theory, tensor space models have been widely developed and effectively applied.

Use relevant algorithms that support tensor machines to analyze relevant patient data, and compare model accuracy of different algorithms. Choose the model with the highest accuracy and integrate it into the database system to help doctors analyze different patient information. State testing and classification are designed to help The doctor treats the patient correctly. Research on related support vector machine classification models and their application in data analysis of Alzheimer's disease is of great significance to disease diagnosis and clinical treatment. At the same time, it also provides a theoretical basis for studying the application of mechanical learning in the field of biomedicine, and has more bioinformatics significance for the development of Alzheimer's disease, which is the correct diagnosis of Alzheimer's disease, especially the early mild cognitive function The correct diagnosis of disorder (MCI) provides a theoretical basis and is necessary for the timely detection and treatment of Alzheimer’s disease.

Aiming at the problem of tensor regression, Tylee D S proposed a least squares support tensor regression machine based on Zhang quantum matrix. LS-STRM-SMT is a method that can deal with tensor regression problems more effectively. First, he developed a least squares support matrix regression machine and proposed a fixed-point algorithm to solve it. Then LS-STRM-SMT for tensor data is proposed. Inspired by the relationship between light color and gray images, he reconstructed the training set of tensor samples and formed a new model of tensor regression. But the whole calculation process is very complicated, which will cause some errors in the results [1]. Magnetic resonance (MR) imaging technology has become an indispensable technology in image-guided diagnosis and clinical research. Kahali S proposed a new technology based on three-dimensional (3D) Gaussian surface convolution, called "Co3DGS", for volume IIH estimation and correction of 3D brain MR image data. Use the local voxel gradients on each tissue volume corresponding to the gray matter, white matter, and cerebrospinal fluid phase of the 3D brain MR image data to approximate the 3D Gaussian surface, then perform convolution to partially estimate the IIH, and then extract it from the image data delete. Repeat the above process until the voxel gradient does not change significantly. However, current MR image acquisition results in slowly varying intensity inhomogeneities in MR image data [2]. The histopathological features of dementia have been described postmortem in the brains of Alzheimer's disease (AD) patients. Agustín Riquelme studied the t-tau and p-tau levels and the subcellular distribution of t-tau in olfactory neuron precursors obtained by nasal stripping in AD patients and control participants. The data shows that the levels of t-tau and p-tau in the cell homogenate of AD patients are elevated. However, due to the unstable factors of the elements in the cells, the accuracy of the data results obtained is not high [3].

The innovations of this article are: (1) When dealing with tensor data, it is an effective method to construct tensor models using tensor kernel functions. This method can be transplanted to models of multiple carrier types. (2) The application of functional magnetic resonance imaging technology to study the abnormal changes of the anatomical structure and function of AD patients and the relationship with cognitive dysfunction is expected to provide a more reliable imaging basis for the timely diagnosis of AD.

2. Support Tensor Machine Magnetic Resonance Imaging Method

2.1. Support Tensor Machine Algorithm

Support vector machine (SVM) is based on minimizing structural risk and introduces core functions that play an important role in solving small sample, high-dimensional, non-linear, minimum value and other problems [4]. However, supporting media machines take delivery samples as input and have limitations when encountering size issues. When studying the problem of small sample categories and the appearance prediction of tensor machines, the first question is about the idea of supporting tensor machines. This method directly receives tensor data as input. Under the condition of allowing the number of classification errors, it aims to find the best gradation trend in the tensor space. The upper structure should make the distance between the two types of supports (closest to the support surface) The longest is [5].

The high-level tensor training sample can be set as:

$$\{X_i, Y_i\}, i = 1,2,..., N \tag{1}$$

The M order tensor data is represented by X_i, the classification label is represented by Y_i, the number of training samples is N, and the formula for constructing a classification hyperplane is as follows:

$$X \prod_{k=1}^{M} \times_k u_k + b = 0 \tag{2}$$

Among them, the parameter waiting for training is represented by b as $\times_k$, which is the symbol of the product of tensor and vector modulus. The interval between the training sample closest to the tensor hyperplane and the hyperplane is 1 [6], and all training samples are as follows:

$$Y_I (X \prod_{k=1}^{M} \times_k u_k + b) \geq 1, (i = 1,2,..., N) \tag{3}$$

Some deviation values are allowed, and Slack variable ψ and penalty factor C are introduced, and the optimization is as follows:

$$\min_{u_k, b, \psi_i} \frac{1}{2} \| u_k \|^2 + C \sum_{i1}^{N} \psi_i \tag{4}$$

Satisfy:

$$Y_I (X \prod_{k=1}^{M} \times_k u_k + b) \geq 1 - \psi_i, (\psi > 0, i = 1,2,..., N) \tag{5}$$

Use the alternating projection algorithm to solve the optimization problem (3)-(5), the specific steps are as follows:

Step 1: Initialize all vectors to 1.

Step 2: Make $j = M$.

Step 3: Set the parameters, then the order tensor sample is transformed into a vector [7-8], and the optimization problem (3)-(5) is transformed into:

$$\min_{u_j,b,\psi_i} \frac{1}{2} \| u_j \|^2 + C \sum_{i1}^{N} \psi_i \tag{6}$$

Step 5: Repeat the above three steps until the u_k and b obtained in the previous cycle are completely close to the current cycle. After solving the optimization problems defined in formulas (3) to (5), the tensor hyperplane (1) is determined, and the tensor samples can be predicted by the following classification function.

$$f(x) = sign(X \prod_{k=1}^{M} \times_k u_k + b) \tag{7}$$

2.2. Recursive Feature Elimination Method

For small sample and high-dimensional sorting problems, the selection of features plays an important role in avoiding excessive positioning and improving classification efficiency. According to the relevance of classification, different weights must correspond to different features [9]. Strong correlation gives higher weight, weak correlation gives lower weight, and non-correlation weight is 0. Recursive feature elimination (RFE) is also used to classify cancer cells [10]. It is a method of selecting features, which can gradually eliminate unnecessary or unrelated information. It is usually used in combination with quantifiers. Among them, SVM-RFE algorithm combined with supporting media machine is a standard feature selection method [11]. Use support vector machine to train and test the model, calculate the level of each function classification standard, delete the lowest level function, and then use the remaining training and test functions to select the next iteration, and finally select the best function [12].

The STM-RFC function selection method used in this article is a combination of retroactive function deletion algorithm and support vector machine. For high-voltage training samples, assume the feature weights of each model trained by the support vector machine [13]. In the whole process, the new feature subset is used as the input of the auxiliary feature machine to obtain the weight distribution of the target feature feature [14].

For features with higher classification coefficients, a single feature may not be able to obtain better classification results. Please note that a combination of multiple functions may be required to achieve the goal [15]. Use the attribute classification list to define many $G_1 \in G_2 \in ... \in G_n$ attribute subcomponents to train the support vector machine, and evaluate the advantages and disadvantages of these subgroups and the accuracy of the predictive support vector machine, so that we can get the best feature subset of each model [16].

2.3. Magnetic Resonance Diffusion Tensor Imaging

When calculating the ADC value of the apparent diffusion factor image, the imbalance of water molecules should also be considered. Under normal circumstances, the proton diffusion process is rarely hindered to varying degrees [17]. For example, when a drop of blue ink drops into water, the speed at which the blue ink diffuses in all directions will be the same [18-19]. However, the tissues of living organisms are not as uniform as water. Some cell membranes are more permeable, while others are less permeable, so Brown's proton motion is restricted in certain directions, which limits the dispersion of water molecules. In human tissues, due to the long fiber structure, the diffusion rate of protons in all directions is different [20]. Generally speaking, if the proton is dispersed in the direction of the long fiber, its speed is faster than the diffusion speed in the vertical direction of the fiber, resulting in anisotropy [21]. However, the apparent dispersion factor (ADC) only represents

the dispersion characteristics imposed by the dispersion rate in a specific direction, and cannot represent the dispersion characteristics that accurately reflect the imbalance of proton motion. In order to reflect the anisotropy, we proposed the display of diffusion capacitor and magnetic coordination diffusion capacitor (DTI) [22].

The dispersion of water molecules in biological tissues is a three-dimensional process, and the diffusion rate in different tissues is different. Therefore, the dispersion rate in various directions will be inconsistent [23]. For example, the speed along the long axis of the fiber is fast, but the speed in the vertical direction is slow. It is precisely because of the unbalanced dispersion of water molecules in biological tissues that we can no longer use a single dispersion rate to describe the dispersion characteristics of water molecules, but the information we need can completely describe the direction and direction of water molecules in different directions in the tissue [twenty four]. Intel, this is the diffusion tensor. First, due to the existence of imbalance, the formula is expressed as:

$$S = S_0 \bullet e^{-\sum i=x,y,z \sum j=x,y,z b_{ij} D_{ij}} \tag{8}$$

Where the diffusion tensor D is expressed as:

$$D = \begin{bmatrix} Dxx & Dxy & Dxz \\ Dyx & Dyy & Dyz \\ Dzx & Dzy & Dzz \end{bmatrix} \tag{9}$$

It can be seen from formula (8) that when calculating the dispersion tensor, multiple weighted dispersion images with different oblique directions need to be collected [25]. Usually, in the process of displaying diffusion capacitance, we use diffusion-sensitive pulse sequence, such as sound level sequence (EPI). Since the diffusion tensor is a two-type symmetric matrix, at least 6 weighted diffusion images with different tilt directions and one non-diffusion S_0 image (b=0) should be collected for the calculation of the tensor. The selection range of drift-sensitive directions is 7-53 [26]. By optimizing the spatial direction of the sensitive slope or increasing the number of slope directions, image noise can be reduced, thereby improving the accuracy of the monitoring of nerve fiber bonds. The more the direction of the dispersion slope is adjusted, the higher the signal-to-noise ratio of the resultant image, and the stronger the ability of the image to describe small fiber bundles. At the same time, the greater the tilt direction, the more accurate the calculation of the fiber monitoring direction, and the more reliable the appearance of the fiber bundle spatial structure. It is concluded through experimental analysis that as long as the tilt direction is optimized, using more tilt directions will not be of great benefit to imaging.

2.4. Support Vector Machine Classification

With the progress of society, the theory of statistical learning has also been continuously developed. Some old mechanical learning algorithms, such as neural networks, cannot effectively overcome the difficulties of solving problems and cannot respond to the situation at the time. On this basis, many researchers have proposed and implemented some improved support vector machine algorithms to solve some problems encountered in real life. Since support vector machines can handle small sample problems, they have great advantages in solving high-dimensional problems. They have been widely used in the processing of classification problems and have become one of the current research hotspots in the field of machine learning.

(1) Linear separation

The initial research object of support vector machine is linear separation state. In different spaces,

the representation of the optimal classification surface is different. For example, a point is used to represent the best classification surface in a single space, a straight line is used to represent the best classification surface in a two-dimensional space, and a curved surface is used in a three-dimensional space. In the high-dimensional space, the superstructure is used to represent the best classification surface.

(2) Linearity is indivisible

The above optimal level is for the linear separation state. In many cases, we will face a linear split. Currently, we can use relaxation factors to solve this problem. After introducing the relaxation coefficient, the super plane should be:

$$f(x) = \text{sgn}(\sum_{sv} y_i a_i^* \cdot (x, x_i) + b^*) \tag{10}$$

When solving nonlinear problems, researchers usually map samples into a high-dimensional space, where the best hyperplane can be found. This mapping process can be implemented through a kernel function, so the double problem is:

$$w(a) = i\sum_{i=1}^{l} a_i - 1/2\sum_{j=1}^{l} a_i a_j y_i y_j L(x\ x_j) \tag{11}$$

3. White Matter Image-Assisted Diagnosis Experiment

3.1. Image Extraction Experiment of Brain White Matter Region

(1) Image preprocessing

To extract the soft tissue part of the brain, first, we create a two-dimensional model to remove other areas of the brain tissue, such as brain bones and hair, and prepare for the extraction of white matter areas. First, we set a relatively small threshold to eliminate the background part of the MRI image to form a binary image. Then four connected regions are marked in the binary image, and the largest connected region is selected as the model of the two-dimensional brain image. However, since there is also a small amount of very low gray in the cerebrospinal fluid, it is easy to treat it as a background area and eliminate it. Here, we use the first expansion function and then the corrosion function to fill the blank area in the binary standard. Finally, use this binary mode to multiply the initial image to extract the soft tissue part of the two-dimensional image of the brain, as shown in the figure below. To export the 3D standard, we use the Bet (Jenkinson) toolbar to export directly.

(2) 3D segmentation experiment

In order to improve the performance of Random walks, we downloaded the corresponding test data from the Brainweb website. This website was created by the China Laboratory Research Laboratory. It provides various magnetic resonance image data in different ways and provides manual fragmentation results of white matter, gray matter brain and cerebrospinal fluid, which can better evaluate the accuracy of the fragmentation results. At the same time, the website also provides a set of MR data with a gray scale ranging from 10% to 40%, so that we can also verify the authenticity of the algorithm in a bias magnetic field. Because this experiment uses weighted T1 to segment the image, I downloaded the relevant phase data set T1 from Brainweb, the size is 163*221*179, and the physical distance is 1mm*1mm*1mm. At the same time, in order to quantify the experimental results, we used the equivalent factor to compare the experimental results of different methods. D can be expressed as:

$$D = \frac{2\times(EX \cap RE)}{EX + RE} = \frac{2\times CO}{2\times CO + ER + FN} \tag{12}$$

EX represents the result of segmentation, RE represents the result of manual segmentation by experts, CO represents the area where the foreground is correctly segmented, ER represents the area where the background is incorrectly segmented, and FN represents the area where the background is correctly segmented. $\cap$ represents the foreground overlap area between the segmentation result and the expert manual segmentation result, and $\cup$ represents the foreground merged area of the two. D ranges from 0 to 1, where 1 represents the segmentation result is exactly the same as the real result of the expert segmentation, and 0 represents a complete segmentation error.

3.2. Establishment of Auxiliary Diagnosis Model

The main steps to determine the auxiliary diagnosis model are: first download the fields we are interested in from the ADNI database, and then we must perform data cleaning on the received raw data. Data cleaning is to improve the quality of initial data through specific methods. Common data quality problems include incomplete data, duplicate data, and data that does not conform to common sense. Subsequently, through a simple bass algorithm and an SVM support engine, some general models of mechanical learning classification were established. The multiple K-fold method was used to verify the accuracy of the model. Calculate each accuracy rate according to the model control group designed in this paper. At the same time, perform PCA reduction analysis on the data you downloaded from DNA to restore the data to three dimensions, then use the Adaboosting algorithm to model the dimensionality reduction data, and cross-validate the established machine classifier K-fold learning analysis algorithm Accuracy. If the accuracy of the algorithm is not high, select a new base classifier, redefine the model, and then calculate the accuracy of the new model.

4. Alzheimer's Diagnosis Analysis Based on Supporting Tensor Machine Algorithm and 3D Brain White Matter Images

4.1. Support Tensor Feature Analysis of White Matter Images

In this experiment, the gray-scale tensor feature of the brain white matter image is used as input, and the support tensor machine is used as the classifier and the STM-RFE performs feature selection and then uses two methods to support tensor classification. The results are shown in Figure 1. From the data in the figure, it can be seen that the classification results of the four groups of experimental populations have been significantly improved after feature selection using the recursive feature elimination algorithm. In particular, the area under the ROC curve (AUC), accuracy (ACC), sensitivity (SEN), and specificity (SPE) in the two groups of AD vs NC and MCI-C vs MCI-NC increased by more than 10% respectively. It is concluded that the recursive feature elimination algorithm effectively removes some redundant information and selects the optimal feature subset, which improves the performance of the classifier.

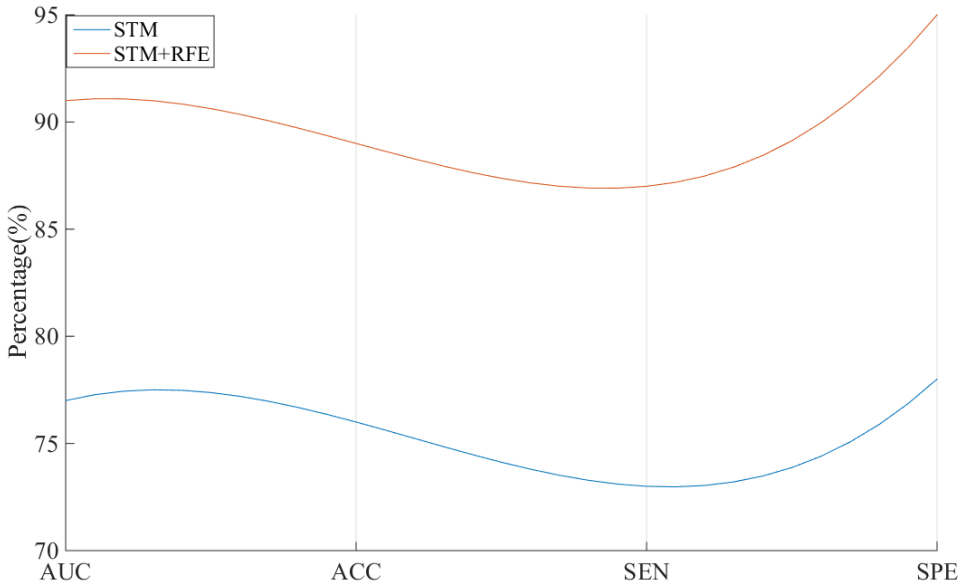

Figure 1. Comparison of SMT and SMT+RFE experimental results

Studies have shown that the combination of multimodal features can increase the detection rate of AD. However, this also means that patients need to do a large number of complicated and expensive examinations such as cerebrospinal fluid (CSF) and PDG-PET, which causes a heavy mental and economic burden on patients. In clinical practice, doctors usually give patients some simple neuropsychological tests as an auxiliary diagnostic basis, such as a simple mental status checklist and Alzheimer's cognitive assessment scale. We call MMSE and ADAS-Cog cognitive scores. The patient's basic information (age, gender, education level) may also provide some useful information for AD diagnosis, so we added the sample's cognitive score and basic information on the basis of the gray tensor feature to conduct experiments. At the same time, observe the result of classification with basic information or cognitive score as the input of support vector machine, and combine the cognitive score with the gray tensor, and the gray tensor combined with the cognitive score and basic data as the input of the support tensor machine The experimental results are compared, and the results are shown in Table 1:

Table 1. Experimental results of different characteristics

	NC vs AD	MCI vs AD	MCI vs NC	MCI-C vs MCI-NC
Method	AUC	ACC	SEN	SPE
A	60	60	63	73
B	98	80	77	75
C	91	74	78	80
D	99	82	92	86
E	99	84	94	82

In the table, method A represents the result of classification using basic information as the support vector machine input; method B represents the result of classification using the cognitive score as the input of the support vector machine; method C represents the gray tensor as the input of the support tensor machine Classification result; Method D means combining gray tensor and

cognitive score, first using STM-RFE algorithm for feature selection, and finally using support tensor machine for classification results; Method E means combining gray tensor and cognitive score And the basic data, first use the STM-RFE algorithm for feature selection, and finally use the support tensor machine to classify the results. The column chart corresponding to each group of experiments is shown in Figure 2:

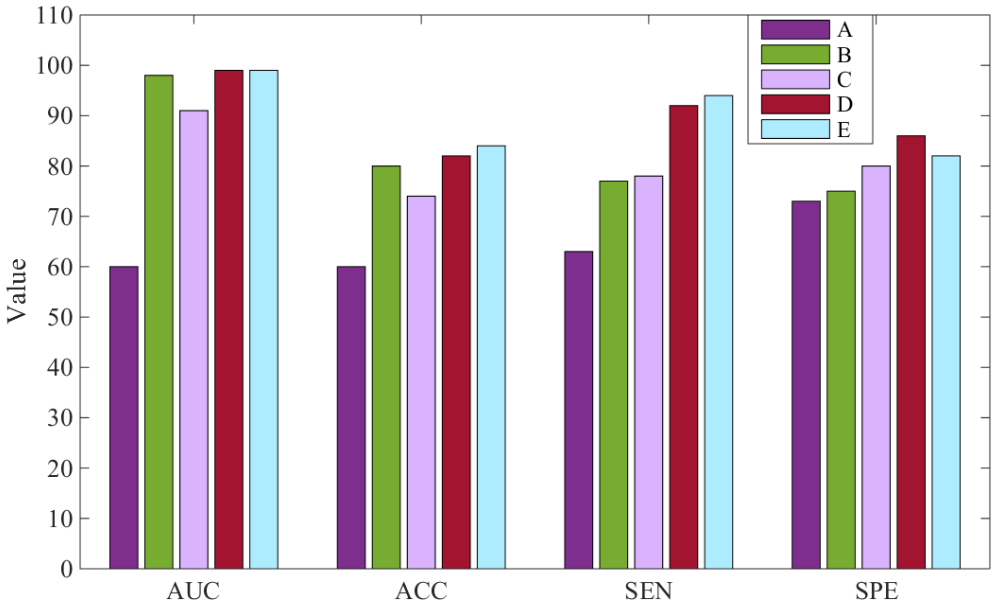

Figure 2. Supported tensor machine classification results

Comprehensive analysis shows that, in a single feature, the cognitive score and gray-scale tensor feature play a great role in classification, and the combination of multiple features has a higher classification accuracy than a single feature. This shows that multiple modal features provide complementary information, and combining these features can improve the performance of the classifier.

4.2. Brain White Matter Image Extraction and Analysis

This article uses the same method to segment the images from No. 81 to No. 100 in Brainweb in two dimensions, and compares the segmentation results of various methods with the average Dice similarity measurement of 30 images, as shown in Table 2. Similar results can be seen from the table. The original Random Walks algorithm cannot extract the various regions of the brain and soft tissues well. After adding the prior probability model and the local binary model, the segmentation performance of the Random Walks algorithm has been greatly improved. It can be seen that the improved algorithm proposed in this paper can extract the white matter region of the MR image very well.

Table 2. Comparison of average D coefficients of 30 images under different algorithm segmentation

	RW	PPRW	LBPPPRW
WM	0.712	0.9077	0.9938
GM	0.2807	0.8875	0.9604
CSF	0.2096	0.8257	0.9134

In order to quantify the comparison results, we still download the T1 synthetic data set from

Brainweb. In order to be closer to the real data, we downloaded the data with 3% noise and 20% magnetic deflection field. And use the Bet (Jenkinson,) toolbox for preprocessing to obtain the brain soft tissue area. Then use the LBP_PP_RW algorithm proposed in this article to segment it, and compare it with the segmentation results of the commonly used software SPM8 (Ashburner) for brain tissue segmentation, as shown in Figure 3:

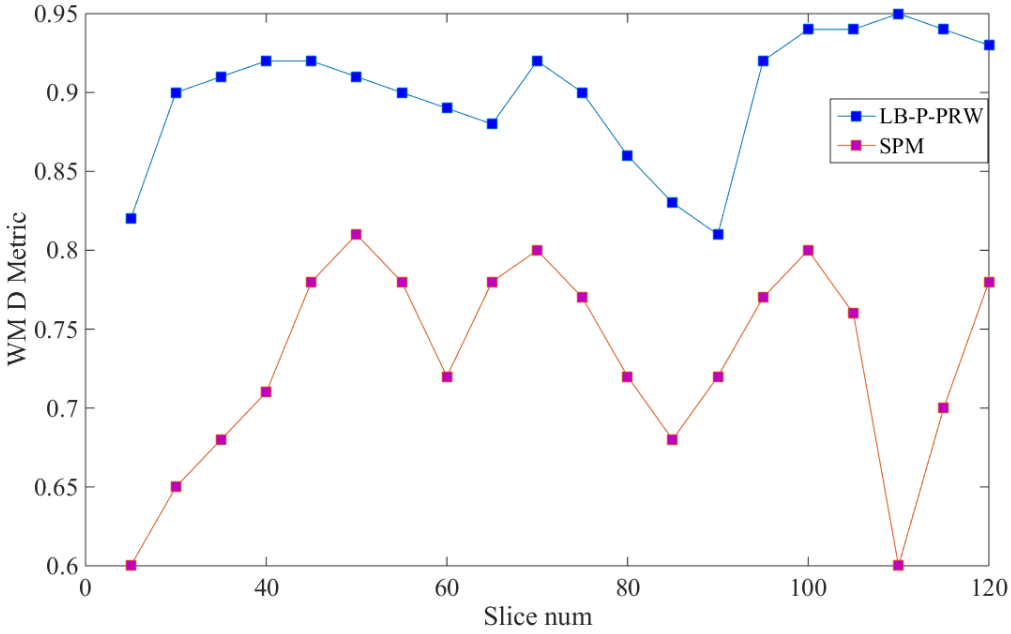

Figure 3. Comparison of layers D of brain white matter

Each layer D of the 3D segmentation results is compared separately. Since some layers have no brain soft tissue, the number of comparison layers is set between 30 and 150. From the data in the figure, it can be seen that whether it is extracting white matter, gray matter or cerebrospinal fluid, the algorithm in this paper has better segmentation results than SPM8. In particular, the accuracy of brain white matter segmentation is basically maintained at more than 90%, indicating that the algorithm proposed in this paper is very suitable for the white matter extraction process.

4.3. Analysis of Alzheimer's Disease Diagnosis Methods

The more feature modes, the better the classification performance. Cognitive scores or three-level grayscale tensors can be used as features to classify can achieve good results, and the combination of the two can greatly improve the classification performance, and the improvement is more in the recognition of MCI-NC and MCI-C-MCI-NC Advantage. Even if combined with basic information data, the classification performance has been improved, but the effect is not so obvious, and the classification effect is relatively poor using only basic information (age, gender, education level) as features. This shows that the cognitive score and gray matter grayscale play a major role in the diagnosis of Alzheimer’s disease, while the basic information data has relatively low correlation with Alzheimer’s disease, but it also contains effective information. Different types of data provide complementary information, combined with different modal data for classification, which is helpful for the diagnosis and treatment of Alzheimer's disease or mild cognitive impairment.

This paper proposes a method for identifying Alzheimer’s disease based on the loss function of the similarity matrix. It divides the MRI and PET brain image data into several regions of interest, and combines the cerebrospinal fluid data to form a feature vector. The similarity matrix method is

used to select the main features.

Then use support vector machine for classification. For the classification of AD-NC, MCI-NC, and MCI-C-MCI-NC, Shen-MPC (combined with MRI, PET and CSF data) has a higher classification accuracy rate than Shen-M (only MRI data). The data of different modalities provide complementary information, which helps to improve the classification performance, but it also requires that every patient has to do MRI, PET examination and cerebrospinal fluid examination to achieve an effective diagnosis. Not only is the examination cost high, it also increases the patient's Psychological burden and negative physical effects are more difficult to achieve clinically. Compared with Shen's method, the tensor-based method based on MRI brain images (Pro-posed-M) presented in this article has a lower accuracy rate of AD-NC classification (but also has an accuracy rate of more than 90%), the other two classifications are better than Shen's. When the method in this paper combines MRI brain image data, Cognition and basic information data, the classification accuracy rate is significantly better than Shen's result, as shown in Figure 4:

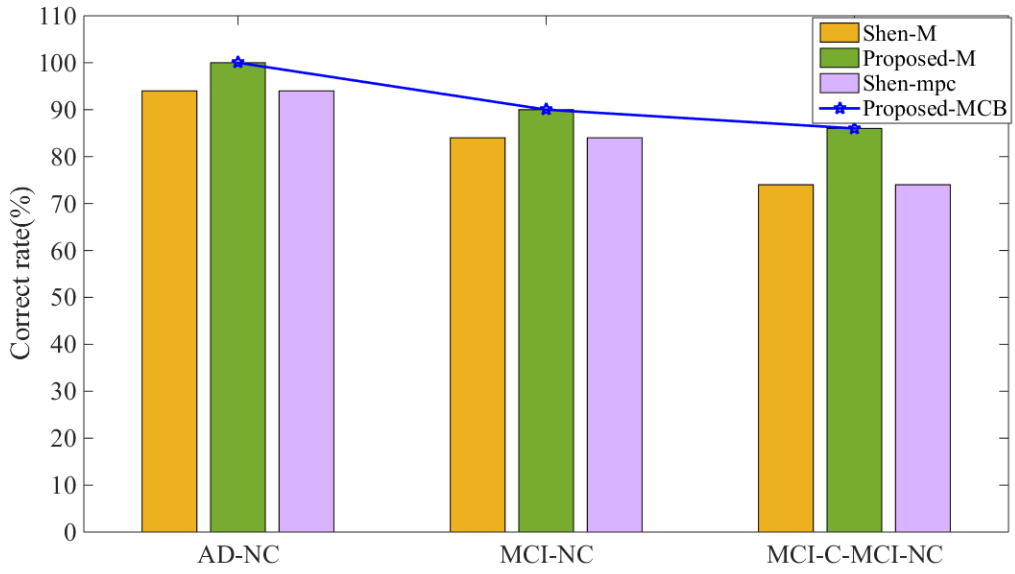

Figure 4. Comparison between the method in this paper and the Shen method

The method in this paper only needs to use MRI brain images, basic information, and cognitive score information, which means that patients only need to do MRI and cognitive score tests. Compared with Shen's method, this can not only reduce the patient's examination items and reduce the cost of medical treatment, but also reduce the negative impact of physical examination on the patient's psychology and physiology, which is easier to achieve clinically.

5. Conclusion

This paper proposes a method for Alzheimer's disease classification based on support vector machines, which uses 3DT1 as input to receive white matter images. First, use the VBM8 toolbar in the SPM8 software to automatically segment the entire brain image into three parts: gray matter, white matter, and cerebrospinal fluid. Then output the gray value of each voxel of the brain white matter to create a gray three-level capacitor. Then use the reverse feature deletion method combined with support vector machine for feature selection, and finally use support vector machine for classification.

Compared with traditional vector space engineering learning, the algorithm proposed in this paper takes initial high-voltage image data as input, which maintains the integrity of data structure

information and avoids small sample events and event data that may be caused by cross-sectional planning. In addition, the algorithm uses a feature selection algorithm that combines retrospective feature elimination with support vector machines, which effectively eliminates unnecessary information, selects the best subset, and improves the efficiency of the classifier.

For the evaluation and comparison of the algorithms in this paper, although we can verify the accuracy of the algorithms by synthesizing simulation data, we have no gold standard for evaluation when verifying the results of actual data. To solve this problem fundamentally, we must also look at the geometric properties of the direction field of nerve fibers from the principles of physics or biology. Therefore, the determination of the gold standard of white matter fiber monitoring algorithm is also a problem worthy of further discussion.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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