Multiple Anatomical Brain Networks for Self-esteem Related Analysis Among Young Adults

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Research

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Abstract

Background: Self-esteem is the individual evaluation of oneself. People with high self-esteem have mental health and can bravely cope with the threats from the environment. With the development of neuroimaging techniques, researches on the cognitive neural mechanisms of self-esteem are increased. Existing methods based on brain morphometry and single-layer brain network cannot characterize the subtle structural differences related to self-esteem.

Method: To solve this issue, we proposed multiple anatomical brain network framework based on multi-resolution ROI template to study the cognitive neuroscience mechanism of self-esteem. Multiple anatomical brain network consist of high-resolution ROI features extracted from structural MRI and hierarchal brain network features. For each layer, we calculated the correlation relationship between pairs of ROIs. In order to solve the high-dimensional problem caused by the large amount of multiple network features, combined feature selection methods are adopted to reduce the number of features while retaining discriminative information to the maximum extent. Multi-kernel SVM is employed to combine the two types of features by appropriate weight coefficient.

Result: Our experimental results show that the proposed method can improve classification accuracy to 97.26% compared with single-layer brain network.

Conclusions: This article reveals the cognitive neural mechanism of self-esteem and provides foundation for positive and healthy self-esteem.

Background

Self-esteem is regarded as self-affirmation and self-identification about themselves [1]. The researchers found that the brain structures of adolescents with different self-esteem levels have differences. Adolescents with good mental health have a higher self-esteem and think of themselves as valuable persons [2]. These people feel that they deserve to be respected by others, and are more able to accept the individual's deficiencies [3]. However, people with low self-esteem have low self-confidence, and the outside world will have a great impact on them, resulting in low socioeconomic status and poor physical health. Neurophysiology research found that self-esteem may be composed of multiple subsystems that are structurally separated from each other but functionally interact [4]. Brain imaging studies suggest that self-esteem involves multiple psychological processes, including self in perception, memory, and introspection. These psychological processes have their own corresponding brain regions. For example, self-face recognition occurs in the right brain, and autobiographical memory is mainly related to the hippocampus, and self-reference is related to the medial prefrontal lobe [5]. In addition to these independent brain regions, the difference in self-esteem is also reflected in the brain network connection. Three networks are activated during the process of self-endorsement traits, mainly distributing in dorsomedial prefrontal cortex, ventromedial prefrontal cortex, and posterior cingulate cortex [6].
Therefore, in this study, we focus on exploring the differences between brain networks of adolescents with different levels of self-esteem.

Brain network aims to study the interaction of various brain regions as a whole, which has an important role to have a deep understanding of brain structures and cognitive neural processes. The anatomical brain network mainly uses the region of interest (ROI) of the brain as the node, and the correlation between brain regions as edge [7-8]. The definition of ROI is a key step in anatomical brain network analysis. Most existing methods use ROI-based brain network analysis methods to study brain structure and functional connections related to self-esteem. Kelly et al. use the functional near-infrared spectroscopy (fNIR) based cerebral blood flow imaging method to estimate the hemodynamic response function of each ROI, in order to study the brain networks that are activated during the processing of self-esteem related information [9]. Goldin et al. use functional magnetic resonance imaging (fMRI) technology to measure changes in the brain network between the self-esteem group and the self-confidence group by measuring the BOLD response in the ROI [10]. Chavez et al. conduct a psychophysiological interaction analysis to calculate the correlation between specific ROIs related to self-esteem [11]. Although a variety of neuroimaging methods can be used to explore the cognitive mechanism of the brain structural magnetic resonance imaging (sMRI) is widely used in the analysis of brain anatomical networks due to its high resolution of brain soft tissue imaging [12]. Studies based on sMR show that self-esteem involves multiple networks related to self-reference processing, autobiographical memory, and social cognition, including default mode networks and social cognition networks [13]. In addition, self-esteem shows the brain network mechanism dominated by bilateral brain and mainly controlled by right brain [14]. Although the above researches have initially revealed the brain network representation of self-esteem, it only used single-network that cannot fully identify the subtle differences in network connectivity caused by self-esteem.

In order to better describe the network representation of self-esteem, enhanced feature representation method is required to better examine function connectivity related to self-esteem. In recent years, machine learning techniques become a research hotspot in the field of brain network analysis due to its ability to learn laws from data and predict unknown data [8]. Brain network analysis can help us fully understand the cognitive psychological activity of self-esteem. However, there are few studies using machine learning methods to construct self-esteem related brain networks, especially for the construction of multi-layer brain networks. In this article, we propose a novel multiple anatomical brain network construction method based on multi-resolution ROIs, which can better describe the correlation between small brain regions and large brain functional areas simultaneously.

**Methods**

**Subjects**

The structural sMRI data used in our study were acquired from the Soochow University, which is composed of 68 adolescents. The study was approved by the Ethics Committee of the Third Affiliated
Hospital of Soochow University. Written informed consents was obtained from all subjects. Each subject was interviewed by a psychologist to rule out any mental or neurological diseases. No subjects had received stimulant or hypnotics before. All participants’ vision was normal or corrected to normal, and they were right-handed. After the test, each participant will receive a small gift or financial reward. All subjects are required to perform Rosenberg Self-esteem Scale (RSES) test. The RSES is originally developed by Rosenberg in 1965 to assess the overall feelings of adolescents about self-worth and self-acceptance. It is the most used self-esteem measurement tool in the psychology community [15]. We ranked the RSES test scores from highest to lowest, and then divided them into two groups: high self-esteem group and low self-esteem group. Table 4 provides detailed information of all participants.

**Imaging acquisition and preprocessing**

All images were collected on a 3T Siemens Medical Systems equipment. The acquisition parameters are set as: echo time (TE) = 2.98 ms, repetition time (TR) = 2300 ms, flip angle (FA) = 9 deg, voxel size = 1 × 1 × 1 mm³, slice thickness = 1 mm, field of view (FoV) = 256mm.

We use an automatic pipeline for sMRI image processing. Firstly, we adjusted the image orientation (axial, coronal, and sagittal) to match the template image, and performed offset field correction to remove the gray-scale unevenness of the image [19]. Secondly, the brain was extracted by removing the skull and cerebellum [20]. Thirdly, gray matter (GM), white matter (WM) and cerebrospinal uid (CSF) were segmented from the background [21]. Fourth, the segmented image was registered to the template labeled with the Automated Anatomical Labeling (AAL) template [22]. Fifth, in order to calculate the morphological features based on the cortex, the middle layer of the cerebral cortex was constructed [23]. After the whole processing, the morphological measurements of GM volume, WM volume, CSF volume, cortical thickness, and cortical surface area of each ROI were obtained for each subject. It should be noted that we removed 12 subcortical ROIs from AAL template considering that the cerebral cortex contains more neurons.

**Classification framework**

The framework of the proposed classification algorithm based on multi-resolution ROI brain network is shown in Fig. 5, mainly including multiple anatomical network construction, feature selection, and classification. Multi-resolution ROI based multiple anatomical brain network were constructed based on morphological features (volume of different brain tissue, cortical thickness, and cortical surface area). Feature selection can reduce the dimensionality of high-dimensional brain network features, only retaining the features that can maximize the specificity of the subjects. The optimal feature subset can be trained by the classifier as neuroimaging markers representing different self-esteem levels.

**Construction of multiple anatomical networks**

Through the above image processing steps, GM volume, WM volume, CSF volume, cortical thickness, and cortical surface area of each ROI can be obtained from the MRI image of each subject. In order to reduce
individual differences, standardization was performed, dividing the measured value of each ROI by the total intracranial volume, mean cortical thickness, and whole cerebral cortical surface area of the subject. Therefore, we used normalized volume and cortical features to provide a more appropriate representation. More objective measurements can be received by such processing. In order to improve the performance of the classifier, we propose a four-layer hierarchical network framework in this paper. We used brain templates with different ROI resolution in each layer to construct brain network nodes and edges.

Specifically, the bottommost template containing 78 ROIs is defined as \( L_4 \), the remaining three layers are defined as \( L_3 \), where \( L_4 \). A larger value indicates a higher-resolution ROI, which is located in the brain network layer closer to the bottom of the hierarchy. By merging small brain regions into large brain functional areas, the number of ROIs are reduced. In the layer \( L_4 \), there are 36 ROIs by dividing the whole brain into lateral, medial and inferior surfaces. In the layer \( L_3 \), 14 ROIs are defined referring to the anatomical brain structure of central, frontal, parietal, occipital, temporal, limbic, and insula lobe. The specific definition rules of these ROIs can be found in Table 5. It is worth noting that in the first layer \( L_1 \), we study the brain as a whole.

For each layer, correlation between ROIs can be calculated using brain template defined above. Its node correspond to the ROIs in different resolution, and the edge corresponds to the interaction between pairs of ROIs. Take the bottom layer as an example, an 78x78 matrix can be calculated by computing the Pearson correlation coefficient between the \( i \)-th ROI and \( j \)-th ROI. We define

\[
C^4(i, j) = \exp \left(-\frac{(t(i) - t(j))^2}{2\sigma^2}\right)
\]  

(1)

Where \( t(i) \) and \( t(j) \) represent the mean thickness of the cerebral cortex corresponding to the \( i \)-th and \( j \)-th ROIs.

\( \sigma \) is defined as \( \sigma = \sqrt{\sigma_i^2 + \sigma_j^2} \), where \( \sigma_i \) and \( \sigma_j \) represent the standard deviation of cortex for the \( i \)-th and \( j \)-th ROI. Due to the symmetry of the correlation matrix, we only use the upper triangular elements of the matrix \( C^4 \) to construct the feature vector. We connect the 3003 upper triangular elements to form the corresponding feature vector for \( L^4 \). Since the ROIs in the remaining three layers are obtained by merging ROIs in the bottommost layer, the mean and standard deviation of these compound ROIs can be obtained by calculating the average value of all ROIs. The definition of correlation matrix \( C^i \) for other layers is similarly to \( C^4 \). The union of the hierarchical networks is constructed by junction of the four upper triangular correlation matrix into a long vector.

**Feature selection**

In order to reduce the feature dimension and filter out the most discriminative features, we adopted a combined feature selection method. First, we use the statistical t-test method for preliminary selection of features with the significant p value less than the threshold (\( p < 0.05 \)). Then, the redundant features are removed using the minimum redundancy and maximum correlation (mRMR) method, and only the
features that can express the difference between groups in the minimum number are retained [24]. After the above two filter-based feature selections, the machine learning recursive feature elimination (SVM-RFE) method [25] is used to further reduce the feature dimension. After completing the entire feature selection steps, the optimal feature subset is obtained.

**Classification using multi-kernel SVM**

There are two types of features in the multiple brain network, one is the high-resolution ROI features in the fourth layer, and the other is the brain network features corresponding to different layers. Multi-kernel machine learning method can integrate these two types of features into a single classifier. Firstly, a Gaussian Radial Basis Function (RBF) kernel function is used to construct a kernel matrix for each type of feature. Secondly, the two kernel matrices are integrated into the multi-kernel matrix through appropriate weight coefficients [25]. Comparing the results of using linear kernel function and using RBF function (non-linear), we discover that the RBF kernel can significantly improve the classification performance. Therefore, we choose the RBF kernel function to construct the multi-kernel classifier. Finally, the optimal features subset can be obtained.

**Cross-validation**

The nested cross-validation method has been applied in our previous research. In the inner loop, the training set are used to determine the parameters of the classifier. In the outer loop, the testing set is used to evaluate the generalization ability of the classifier. It should be noted that at the beginning of the experiment, the entire data set was randomly divided into two parts, one for training and the other one for testing. The training set and testing set can be exchanged throughout the verification process, while the processing steps remain unchanged.

**Results**

**Classification performance**

Various indexes can be used to evaluate the classification performance of the proposed method (Fig. 1). The evaluation indicators include accuracy, sensitivity, specificity, area under the receiver operating characteristic curve, F score, balanced accuracy, Youden's index are listed in Table 1. The research results show that the multi-layer brain network features have the highest classification accuracy of 97.26%, and the AUC is also greater than other feature types. This indicates that the multiple brain network features have advantages in characterizing structural differences at the global level. In addition, the higher specificity and sensitivity also show that the multiple brain network features have better recognition capabilities in exploring the subtle differences in brain structure caused by self-esteem.

**Weight coefficient**

The role of the weight coefficient is to determine the proportion of the two types of features in the multi-kernel classifier (Fig. 2). Appropriate weight coefficient help the classifier performance the best. A smaller
weight coefficient indicates that the contribution of the fourth-layer fine ROI features is lower, while the contribution of the hierarchical brain network features is higher. Through experiments, we can find the most suitable weight coefficient in the range of 0-1.

The weight coefficient has an important influence on the performance of the classifier. It is proved that the weight coefficient can make the classifier perform well in the relatively large range from 0.05 to 0.35, which can decline the difficulty of determining the ratio of the two features, which reflects the robustness of our proposed method. The best results are obtained at 0.05. At this time, the hierarchical brain network features contributed more to the classification than the high-resolution ROI features in the bottommost layer. This is because the hierarchical brain network can fully express the differences in brain structure between the two groups.

**Top discriminative features**

We use the proposed method to select the most discriminative ROI features (Fig. 3). These ROIs include occipital lobe (superior and middle occipital gyrus, cuneus), frontal lobe (supplementary motor area, middle frontal gyrus), temporal lobe (middle temporal gyrus), parental lobe (precuneus, angular gyrus), limbic lobe (posterior cingulate gyrus), and central region (precentral gyrus). The experimental results also show that differences in brain structure related to self-esteem are mainly in WM and cortical thickness (Table 2).

The top 15 network features selected from all four layers (Table 3). The most discriminative hierarchical network features are mainly distributed in limbic lobe and parental lobe (Fig. 4).

**Discussion**

We studied multiple anatomical brain network related to self-esteem. Our results have demonstrated that the proposed method is superior to the single network method. The multiple networks enhance the representation of the specific brain structure related to self-esteem, thereby providing an effective and novel method to detect self-esteem related biomarkers.

**Improvement of the proposed method**

It is difficult to fully understand the functional organization of the brain using only a single network framework since the brain is a complex system. In this study, we construct a multiple anatomical brain network in multi-resolution ROIs to improve the classification performance. Compared with the single-network based method, multiple networks enhance the classification performance by using supplementary information from different networks. Compared with the best results obtained using a single network, our proposed multiple anatomical network method can improve the classification accuracy by 8.95% (Table 1).

**Analysis of discriminative features**
The discriminative ROI features discovered by our method are distributed in multiple regions of the brain. Because few current studies employ automatic classification method to study the brain structure of self-esteem, we only compare brain regions found through our machine learning method with existing morphological based studies. Compared with previous studies, our results showed consistency in departmental brain regions, including precuneus [4], precentral gyrus [15], middle frontal gyrus [16], cuneus [4], posterior cingulate [17], angular [18]. This indicates the effectiveness of our classification method in revealing brain regions related to self-esteem. In addition to these consistent regions, we also found that the middle occipital, superior occipital, and supplementary motor are related to self-esteem. These brain regions have not been reported in previous studies.

The discriminative network features are mainly located on frontal, parental and limbic lobe. After a comprehensive analysis of existing research on neuropsychological mechanisms related to self-esteem, we found that the frontal region is an important part of the neural basis related to self-esteem. The frontal lobe is responsible for self-evaluation, self-regulation, and emotion management. Individuals with low self-esteem have a stronger emotional response to social evaluations, while high self-esteem individuals show stronger self-positivity in the process of self-evaluation. These findings indicate that frontal lobe plays an important role in generating positive self-information.

**Conclusions**

In this study, we proposed a multiple anatomical brain network based on sMRI among adolescent. Compared with the single network structure, the features extracted from the proposed methods can improve the self-esteem related network representation. Both high-resolution ROI features and the hierarchical network features contribute to the improvement of the classifier. The optimal hierarchical network features provide us a new perspective to inspect the discriminative regions of self-esteem. The results of cross-validation experiments also prove the effectiveness of our method. In subsequent research, other brain cognitive activity research and brain disease diagnosis can be carried out by the multiple anatomical brain networks.

**Abbreviations**

ROI: the region of interest; fNIR: the functional near-infrared spectroscopy; fMRI: functional magnetic resonance imaging; sMRI: structural magnetic resonance imaging; RSES: Rosenberg Self-esteem Scale; TE: echo time; TR: repetition time; FA: flip angle; FoV: field of view; GM: gray matter; WM: white matter; CSF: cerebrospinal fluid; AAL: Automated Anatomical Labeling; mRMR: the minimum redundancy and maximum correlation; SVM-RFE: the machine learning recursive feature elimination; RBF: Radial Basis Function.

**Declarations**

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Author's contributions

BP and YD: proposed the idea, performed experiments and analyzed the data, made discussions and composed the manuscript together with SW and CW. SW: responsible for collecting data and giving clinical guidance. All authors read and approved the final manuscript.

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Availability of data and materials

The datasets used and/or analyzed during the current study are available from the corresponding author on reasonable request.

Ethics approval and consent to participate

The study is approved by the Ethics Committee of the Third Affiliated Hospital of Soochow University.

Consent for publication

All subjects gave written informed consent in accordance with the Declaration of Helsinki.

Competing interests

The authors declare that they have no competing interests.

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Tables

Table 1. Classification performance using different feature types.
| Features (Layer(s))                                      | ACC (%) | AUC (%) | SEN (%) | SPE (%) | Y (%) | F (%) | BAC (%) |
|---------------------------------------------------------|---------|---------|---------|---------|-------|-------|---------|
| Network features in the 4th layer                       | 90.69   | 96.63   | 87.72   | 90.65   | 86.74 | 77.38 | 88.77   |
| Network features in the 3th layer                       | 88.31   | 84.27   | 85.32   | 84.29   | 88.33 | 82.62 | 85.74   |
| Network features in the 2th layer                       | 89.59   | 76.65   | 78.53   | 75.94   | 73.24 | 69.18 | 67.77   |
| Network features in all layers                          | 92.59   | 91.93   | 91.51   | 90.91   | 93.27 | 87.18 | 91.49   |
| ROI features in the 4th layer                           | 88.69   | 85.63   | 87.72   | 87.65   | 86.74 | 77.38 | 88.77   |
| ROI features and network features in the 4th layer       | 94.41   | 95.58   | 94.42   | 93.41   | 92.47 | 92.82 | 92.64   |
| **Multilevel (ROI features in the 4th layer and network features in all layers)** | 97.26   | 99.88   | 97.27   | 97.41   | 97.12 | 94.53 | 97.27   |

*ACC = accuracy; AUC = area under receiver operating characteristic curve; SEN = sensitivity; SPE = specificity; Y = Youden's index; F = F-score; BAC = Balanced accuracy.

**Table 2. Top 15 most discriminating regional features that were selected using the proposed classification framework.**
| No. | Name of ROI                  | L/R | Tissue | Brain Lobe    | Frequency |
|-----|------------------------------|-----|--------|---------------|-----------|
| 1   | Middle frontal gyrus         | R   | WM     | Frontal lobe  | 185       |
| 2   | Superior occipital gyrus     | R   | GM     | Occipital lobe| 144       |
| 3   | Precentral gyrus             | R   | Thickness | Central region| 141       |
| 4   | Middle occipital gyrus       | L   | GM     | Occipital lobe| 102       |
| 5   | Supplementary motor area     | R   | WM     | Frontal lobe  | 86        |
| 6   | Posterior cingulate gyrus    | L   | CSF    | Limbic lobe   | 75        |
| 7   | Middle frontal gyrus         | L   | WM     | Frontal lobe  | 73        |
| 8   | Posterior cingulate gyrus    | L   | Thickness | Limbic lobe  | 70        |
| 9   | Middle occipital gyrus       | R   | Thickness | Occipital lobe| 68        |
| 10  | Angular gyrus                | R   | WM     | Parietal lobe | 64        |
| 11  | Precuneus                    | R   | Thickness | Parietal lobe| 58        |
| 12  | Cuneus                       | L   | WM     | Occipital lobe| 58        |
| 13  | Middle temporal gyrus        | L   | Area   | Temporal lobe | 54        |
| 14  | Precuneus                    | L   | Thickness | Parietal lobe| 53        |
| 15  | Middle occipital gyrus       | L   | Thickness | Occipital lobe| 53        |

L = left hemisphere; R = right hemisphere; GM = gray matter volume; WM = white matter volume; CSF = cerebrospinal volume; Thickness = cortical thickness; Area = cortical surface area; Frequency = selected frequency over 100 repetitions of two-fold cross validation.

**Table 3. Top 15 similarity features that were selected using the proposed classification framework.**
| Network | Name of ROI                                      | L/R | Name of ROI                                      | L/R | No. | Frequency |
|---------|-------------------------------------------------|-----|-------------------------------------------------|-----|-----|-----------|
| Network 4 | Orbitofrontal cortex (inferior)                | L   | Superior parietal gyrus                         | L   | 15  | 45        |
|         | Rectus gyrus                                    | L   | Precuneus                                       | L   | 12  | 48        |
|         | Orbitofrontal cortex (inferior)                | L   | Paracentral lobule                              | R   | 10  | 54        |
|         | Orbitofrontal cortex (inferior)                | R   | Precuneus                                       | L   | 3   | 95        |
| Network 3 | Parietal lobe: Lateral surface                 | R   | Limbic lobe: Temporal pole (superior)           | R   | 1   | 118       |
|         | Frontal lobe: Lateral surface                  | L   | Parietal lobe: Lateral surface                  | L   | 2   | 114       |
|         | Temporal lobe: Lateral surface                 | L   | Parietal lobe: Lateral surface                  | R   | 4   | 93        |
|         | Frontal lobe: Lateral surface                  | R   | Temporal lobe: Lateral surface                  | R   | 5   | 93        |
|         | Frontal lobe: Lateral surface                  | R   | Parietal lobe: Lateral surface                  | L   | 6   | 92        |
|         | Central region: Rolandic operculum              | L   | Limbic lobe: Temporal pole (superior)           | L   | 7   | 74        |
|         | Central region: Postcentral gyrus              | R   | Parietal lobe: Lateral surface                  | R   | 9   | 61        |
|         | Temporal lobe: Lateral surface                 | R   | Limbic lobe: Temporal pole (superior)           | R   | 13  | 47        |
|         | Parietal lobe: Lateral surface                 | L   | Limbic lobe: Temporal pole (superior)           | L   | 14  | 47        |
| Network 2 | Central region                                 | L   | Limbic lobe                                     | L   | 8   | 73        |
|         | Central region                                 | R   | Limbic lobe                                     | L   | 11  | 54        |

L = left hemisphere; R = right hemisphere; Frequency = selected frequency over 100 repetitions of two-fold crossvalidation.

**Table 4. Demographic information of all subjects**
|                  | High self-esteem group | Low self-esteem group | p value |
|------------------|------------------------|-----------------------|---------|
| Subjects         | 34                     | 34                    |         |
| Male/Female      | 19/15                  | 16/18                 | 0.83    |
| Age (mean SD)    | 21.90 1.16             | 22.53 1.42            | 0.77    |
| Rosenberg Scale (mean SD) | 25.35 0.81         | 17.86 3.35            | <0.001  |

The $p$-value of gender was obtained by chi-squared test.

The $p$-values of age and Rosenberg scale were obtained by $t$-test

Significance level was set to 0.05

Table 5. Regions of interest (ROIs) defined in the automated anatomical labeling (AAL) template.
| No. | Name of ROI | No. | Name of ROI |
|-----|-------------|-----|-------------|
| 1, 2 | Central region | 1, 2 | Central region: Precentral gyrus |
| 3, 4 | Central region: Postcentral gyrus | 53, 54 | Postcentral gyrus |
| 5, 6 | Central region: Rolandic operculum | 17, 18 | Rolandic operculum left |
| 3, 4 | Frontal lobe | 7, 8 | Frontal lobe: Lateral surface |
| 9, 10 | Frontal lobe: Medial surface | 19, 20 | Supplementary motor area |
| 11, 12 | Frontal lobe: Orbital surface | 5, 6 | Orbitofrontal cortex (superior) |
| 13, 14 | Temporal lobe | 13, 14 | Temporal lobe: Lateral surface |
| 67, 68 | | 69, 70 | Superior temporal gyrus |
| 73, 74 | | | Middle temporal gyrus |
| Lobe | Regions | Description | Reference |
|------|---------|-------------|-----------|
| Parietal lobe | 7, 8 | Inferior temporal gyrus | 74, 77, 78 |
| Parietal lobe: Lateral surface | 15, 16 | Superior parietal gyrus | 55, 56 |
| | | Inferior parietal lobule | 57, 58 |
| | | Supramarginal gyrus | 59, 60 |
| | | Angular gyrus | 61, 62 |
| Parietal lobe: Medial surface | 17, 18 | Precuneus | 63, 64 |
| Occipital lobe | 9, 10 | Superior occipital gyrus | 45, 46 |
| Occipital lobe: Lateral surface | 19, 20 | Middle occipital gyrus | 47, 48 |
| | | Inferior occipital gyrus | 49, 50 |
| Occipital lobe: Medial and inferior surfaces | 21, 22 | Calcarine cortex | 39, 40 |
| | | Cuneus | 41, 42 |
| | | Lingual gyrus | 43, 44 |
| | | Fusiform gyrus | 51, 52 |
| Limbic lobe | 11, 12 | Temporal pole (superior) | 71, 72 |
| Limbic lobe: Temporal pole (superior) | 23, 24 | Temporal pole (middle) | 75, 76 |
| Limbic lobe: Anterior cingulate gyrus | 25, 26 | Anterior cingulate gyrus | 31, 32 |
| Limbic lobe: Middle cingulate gyrus | 27, 28 | Middle cingulate gyrus | 33, 34 |
| Limbic lobe: Posterior cingulate gyrus | 29, 30 | Posterior cingulate gyrus | 35, 36 |
| Limbic lobe: ParaHippocampal gyrus | 31, 32 | ParaHippocampal gyrus | 37, 38 |
Figures

**Figure 1**

Boxplot of classification accuracy for different feature types. (1) Network features in the 4th layer, (2) Network features in the 3th layer, (3) Network features in the 2th layer, (4) Network features in all layers, (5) ROI features in the 4th layer, (6) ROI features and network features in the 4th layer, (7) Multilevel features.
Figure 2

Classification performance with multilevel ROI features using different weighting factors. The weight for the ROI features decrease from left to right (range from 0 to 1).
Figure 3

The most discriminating ROI features projected onto the cortical surface.
Figure 4

Correlative matrix. (a) high self-esteem group, (b) low self-esteem group. (c) differences between the two groups.
Figure 5

Framework of the classification method using multilevel network features.