

RESEARCH ARTICLE

Skull ethnic classification by combining skull auxiliary image with deep learning

Huijie Sun¹, Junli Zhao^{1,*}, Chengyuan Wang¹, Yi Li¹, Niankai Zhang¹, Mingquan Zhou²

¹ College of Computer Science and Technology, Qingdao University, Qingdao 266071, China

² Engineering Research Center of Virtual Reality and Applications, Ministry of Education, Beijing 100875, China

* Correspondence: zhaojl@yeah.net

Received January 31, 2021; Revised April 17, 2021; Accepted May 3, 2021

Background: China is a multi-ethnic country. It is of great significance for the skull identification to realize the skull ethnic classification through computers, which can promote the development of forensic anthropology and accelerate the exploration of national development.

Methods: In this paper, the 3D skull model is transformed into 2D auxiliary image including curvature, depth and elevation information, and then the deep learning method of the 2D auxiliary image is used for ethnic classification. We construct a convolution neural network structure inspired by VGGNet16 which has achieved excellent performance on image classification. In order to optimize the network, Adam algorithm is adopted to avoid falling into local minimum, and to ensure the stability of the algorithm with regularization terms.

Results: Experiments on 400 skull models have been conducted for ethnic classification by our method. We set different learning rates to compare the performance of the model, the highest accuracy of ethnic classification is 98.75%, which have better performance than other five classical neural network structures.

Conclusions: Deep learning based on skull auxiliary image for skull ethnic classification is an automatic and effective method with great application significance.

Keywords: skull auxiliary image; deep learning; skull ethnic classification; convolutional neural network

Author summary: Skull ethnic classification is of great significance in anthropology, forensic science and archaeology. We put forward a method of ethnic classification which combines deep learning with 2D skull auxiliary image containing depth, curvature and elevation information. The skull features are automatically extracted and classified by our network. Experimental results show that our method can obtain excellent performance of ethnic classification. In the future, we will extend the method to multi ethnic classification.

INTRODUCTION

China is a multi-ethnic country with prosperous national culture. Due to the living environment, genetic and other factors, the appearance characteristics of different nationalities are very different. Skull is an important research object in the fields of forensic anthropology, archaeology, facial reconstruction and so on. Skull is very hard to be damaged and it is easy to preserve skull features, it can better preserve the characteristics, so the identification of gender, race or ethnic through the skull is a reliable method and it has gradually become a

research hotspot. In the criminal cases of forensic anthropology, many corpses are seriously damaged, even leaving only the skeleton, so it is impossible to identify the face and gender. The identification of skull ethnic can help to identify the victim and speed up the process of case investigation. In the field of archaeology, skull is an important unearthed cultural relic, which plays a positive role in understanding the historical development process, excavating the national culture and promoting national unity.

Chinese anthropologists have done a lot of research on the characteristics of different nationalities. In the

1980s, Zhang put forward the research on the physical characteristics of Tibetan people [1], Zhuang people [2] and Li people [3]. In the 1990s, Ai and Zheng respectively studied the physiological characteristics of Uygur people [4] and Hui people [5]. In recent years, the research on the physiological characteristics of Han people in different regions [6–9] has gradually increased. According to the relevant research, there are significant differences between the minority ethnic groups and Han facial appearances [10].

At present, the research on ethnic classification mainly focuses on 2D face images. Li *et al.* [11] used C5.0 algorithm to discriminate three ethnic images of Tibetan, Uyghur and Zhuang ethnicities, with an average accuracy of 90.95%. Compared with 2D face image, 3D skull model is more complex and difficult to obtain, so there is little research on 3D skull data classification of different ethnic (the same race). As the similarity between the ethnic classification and gender identification or race identification of skull, related references are investigated here.

Gender and race classification methods mainly include observation and measurement classification method and computer-aided classification method.

Observation and measurement classification method

In gender identification, Williams [12] identified the gender of European Caucasians by observing the size of mastoid, the structure of supraorbital ridge, the concave convex degree of zygomatic extension and the shape of nostril, with average accuracy of 90%. Walker [13] selected five features including nuchal spine, mastoid process, eyebrow/supraorbital region, supraorbital margin and chin eminence skull for gender classification, and the final accuracy was 88%. In race identification, Zhou and Wu [14] compared the skulls of Chinese and Europeans, and found that the bulge of the canine fossa and the lateral part of the piriform foramen was more likely to appear on the skulls of modern Europeans, while the probability of the zygomatic process appearing on the skulls of Chinese and Europeans was almost the same. Weinberg *et al.* [15] studied about 70 skulls, which were black-and-white fetuses about eight months old. The results showed that the lower occipital bone of white fetuses was narrower than that of black fetuses, and the vomer bone was longer, the anterior nasal spine was prominent, the bone ridge under the nasal bone was thick, and the edge of temporal scale was semicircular.

Although this kind of method is simple, it relies too much on experts' experience and subjectivity, which makes the classification results not objective and accurate.

Computer-aided classification method

In recent years, statistical theory is closely combined with computer technology. The feature extraction from observation and measurement has gradually developed into automatic feature extraction by computer according to statistical algorithm, which makes the gender and race recognition of skull tend to be automated. Literature [16–19] extracted different characteristic variables to establish discriminant equations for race identification, and the accuracy rate of race identification was more than 80%. Yasar and Steyn [17] established discriminant equations for black and white people in Southern Africa, with the highest average accuracy rate of 96.8%. Literature [20–26] used discriminant analysis to identify the gender of different skull features. In 2016, Liu [20] established a discriminant equation for 12 characteristic indexes including nose width and mastoid width, and the accuracy of gender identification could reach 95%. Luo [27] and Yang [28] used principal component analysis (PCA) to establish statistical shape model, and obtained skull feature vector to identify skull gender, and the identification rate was more than 90%. Luo [29] used the method of sparse principal component analysis (SPCA) to extract skull features and find four optimal regions. The final gender identification rate was about 97%.

With the rapid development of computer technology, machine learning methods have been widely used in classification problems. Yang *et al.* [30] combined convolution neural network with least square method to identify gender, and the average accuracy rate was 94.4%. In 2019, Yang *et al.* [31] measured six skull features, including sagittal arc, sagittal chord, sagittal arc, sagittal chord, sagittal arc and sagittal chord, as input of neural network for gender identification, and the accuracy of the test reached 96.764%. In race identification, Joseph *et al.* [32] used random forest algorithm to identify race with multiple features, and the average accuracy was 89.6%. Casper *et al.* [33] used the same feature vector as Luo [27] for race identification, with an average accuracy of 79%.

Compared with other classification methods, deep learning method has stronger learning ability and generalization ability. The operation is relatively simple and fast, and has more application value. Compared with the traditional method, literature [34] uses back propagation neural network for ethnic classification, which improves the automation and convenience to a certain extent. But this method requires researchers to understand the characteristics of different nationalities and extract skull features with significant differences. Because there are many nationalities and races in the world, this is complex and difficult to achieve.

Therefore, in this paper, the deep learning method is used to study the classification of skull ethnic. We propose to transform the Han and Uyghur 3D skull models into 2D skull auxiliary images containing depth, curvature and elevation information, and input them into VGGNet16, which has superior performance in the field of image classification (Fig. 1).

RESULTS AND DISCUSSION

In this paper, 400 skull models were used for Han and Uyghur classification experiments, including 200 Uyghur and 200 Han, and they were randomly divided into 80% train data and 20% test data. We transform the 3D skull data into 2D skull auxiliary images and input them into neural network for experimental analysis. The specific network structure is described in the materials and methods section. At the same time, in order to verify the performance of the network selected in this paper, we compare it with a variety of different convolutional neural network structures.

Experimental results and analysis under different parameters

In the process of network model training, the setting of network parameters is particularly important, which directly affects the results of the network model. The optimal parameter setting is different for different tasks. Therefore, in this section, we select the optimal combination of super parameters for skull ethnic

discrimination task through many experiments. Firstly, we consider the influence of the number of iterations. Because we used small sample data, we controlled the number of iterations between 1 and 40 during the experiment. Then we analyzed the influence of different learning rates on network performance. If the convergence time of loss function is too long, the learning rate can be increased appropriately. When the loss function cannot converge, the learning rate can be reduced appropriately. Through several experiments, the Figs. 2 and 3 show the change of training loss and average training accuracy under three different learning rates when the number of iterations is 40.

It can be seen from Fig. 2 that different learning rates lead to different network convergence rates. On the whole, when the number of iterations is 40, the training loss has decreased to a very small value, indicating that the model has basically reached a stable state. When the learning rate is 0.0001, the training accuracy can reach up to 100%, while when the learning rate is 0.001 and 0.01, the training accuracy can only reach about 50% (Fig. 3). This shows that different learning rates have different effects on the network performance, and choosing the appropriate learning rate can greatly improve the classification effect. Therefore, we set the learning rate at 0.0001.

In addition, we also consider the impact of batch-size on recognition accuracy. Appropriate batch-size can improve training speed and accuracy. Most experiments have shown that GPU can perform better when batch-size is a power of 2. Therefore, this paper sets batch-size

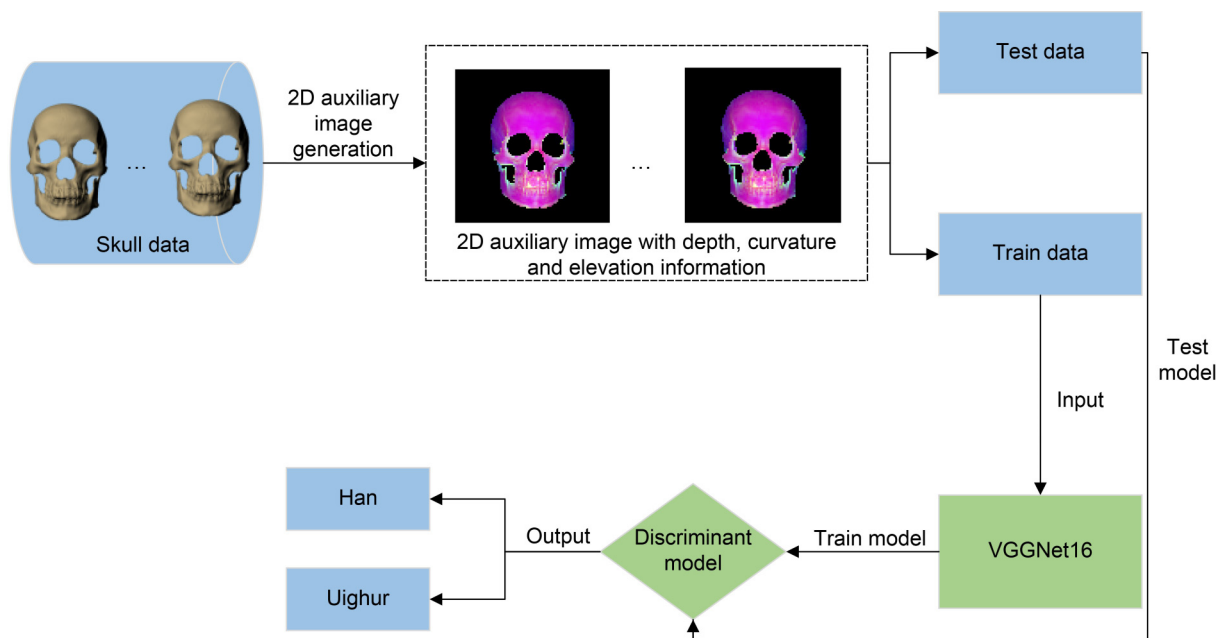


Figure 1. Pipeline of skull ethnic classification.

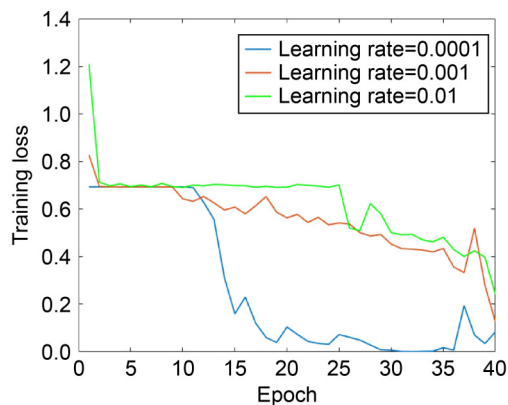


Figure 2. Training loss of our network under different learning rates.

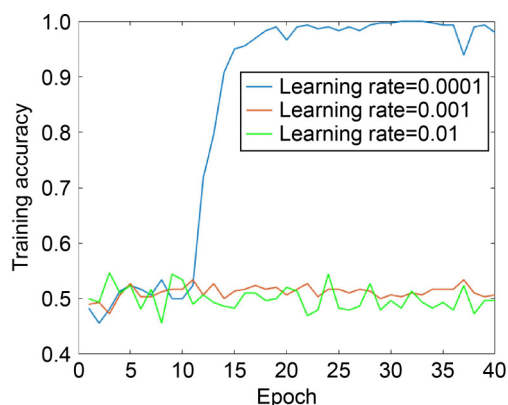


Figure 3. Training accuracy of our network under different learning rates.

to 8, 16, 32, 64 to experiment and record the training accuracy.

The experimental results are shown in Figs. 4 and 5. From the figure, it can be seen that four different batch-size values can achieve the highest training accuracy. When batch-size is 16, accuracy increases the fastest and changes steadily. In summary, the experimental results show that when the learning rate is 0.0001 and the batch-size is 16, the network performance is the best, and it is the optimal combination of network parameters for ethnic discrimination problems. At this time, the accuracy of the network on the test set can reach 98.75%.

Comparison of different network structures

In order to compare the performance of our and other network structures in skull ethnic classification problem, we compare the experimental results of VGGNet19 [35], LeNet [36], AlexNet [37], ResNet [38] and GoogLeNet [39] when the learning rate is 0.0001. The same data are used in the experiments. After 40 iterations, the average

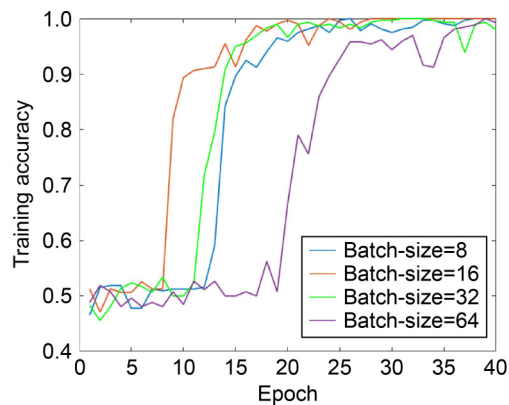


Figure 4. Training accuracy of our network under different batch-size.

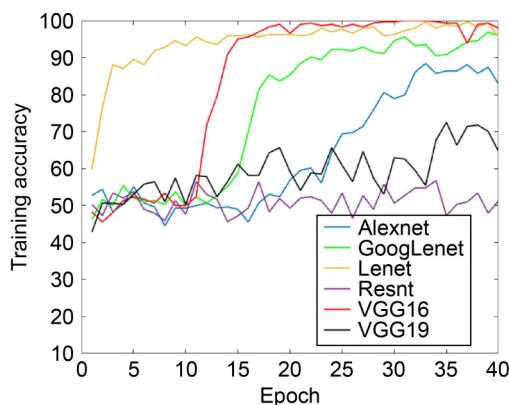


Figure 5. Training accuracy change of different network under same learning rates.

Table 1 Test accuracy rate under different network

Different network	Test accuracy
AlexNet	96.88%
LeNet	93.75%
VGG19	95.31%
GoogLeNet	93.06%
ResNet	84.38%
Our Method	98.75%

training accuracy of each network is shown in the Fig. 4, and the performance of the final network model on the test data is in Table 1.

Figure 5 shows the change in training accuracy when the training data and parameters are the same. LeNet has two convolution layers and three full connection layers, and AlexNet includes five convolution layers and three full connected layers. Their convolution kernel size is $5 * 5$. VGG19 has 16 convolution layers and 3 full connection layers, the convolution kernel size is $3 * 3$; GoogLeNet adopts the improved Inception Module;

ResNet is the ResNet-101 network structure. As shown in Fig. 5, the accuracy of our network used in this paper is significantly higher than that of other image classification networks. The performance of each network in the test data (Table 1) also verifies the superior performance of our method, the accuracy of our network used in this paper is 98.75%. As can be seen from Fig. 6, the accuracy ranked from high to low is our method, AlexNet, VGGNet19, LeNet, GoogLeNet, ResNet. It shows that the small convolution kernel can extract skull features better, and the depth of the network has a great impact on the classification performance of the model. So, our method is more robust to complex data like skull, and more suitable for the study of skull ethnic classification.

CONCLUSIONS

As deep learning is robust to noise and has better generalization, we put forward a method of ethnic classification which combines 2D auxiliary image of skull with deep learning. The 3D skull model of Uygur and Han is converted to 2D image which contains curvature, elevation and depth information as input of convolution neural network. The skull features are automatically extracted and classified by neural network instead of extracting features of different ethnics by hand and can be applied to other different ethnic groups easily and quickly, which greatly improves the generalization ability.

This paper utilizes 16 layers network structure to extract features and classify ethnic. All convolution kernels in the network are as small as 3*3, which reduces the amount of calculation and speeds up the training process. It improves the network performance by deepening the network level, and the final average accuracy is up to 98.44%. Compared with other five network models, our method is superior to the state-of-

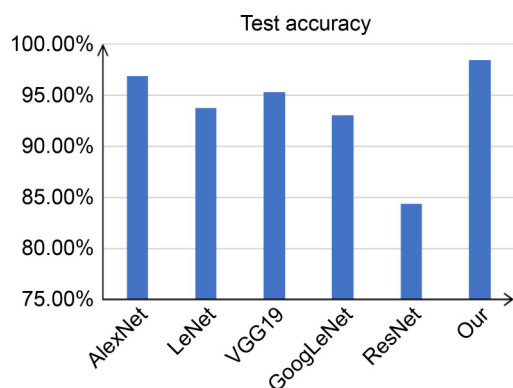


Figure 6. Test accuracy rate under different network.

the-art classification networks, and it is more suitable for ethnic classification.

Due to the limitation of the existing data, we only carried out the classification experiment on Uygur and Han, which will be extended to multi ethnic classification in the future. We will also continue to explore the deep learning methods, continuously try to adjust and explore the optimal network structure, so as to improve the recognition rate and form a more perfect and meaningful automated classification method.

MATERIALS AND METHODS

3D skull dataset

The experimental data used in this paper include 400 non pathological skull CT raw data, of which 200 Han head CT data are from the craniofacial CT database of the Engineering Research Center of Virtual Reality Application Ministry of Education in China; 200 Uygur head CT data were obtained from the radiation center of the people's Hospital of Toxon County, Xinjiang, China. The collected CT images is 512×512 , the color and depth are the same 16 bits. Firstly, the skull contour boundary [40] is extracted from the collected CT data, and then Marching Cube algorithm [41] is used reconstructs 3D model to get 3D skull and face model. The main idea of the algorithm is to detect the voxels intersecting with the iso-surface and calculate the coordinates of the intersection point, and then use the look-up table to construct the mesh topological relations in the voxels for different intersecting situations. Then we need to preprocess the 3D skull model. First, in order to avoid the influence of posture, scale and coordinate system, we adjust all the skulls to the same Frankfurt coordinate system [42]. The Frankfurt coordinate system is determined by the left ear hole point, right ear hole point, left eye orbital lower edge point and eyebrow center point. All skull data can be adjusted to Frankfurt coordinate system by rotation and translation, so that all the skull models can be unified in posture. Second, non-rigid data registration method based on TPS is used for registration [43]. TPS is a region registration algorithm based on the correspondence between feature points calibrated manually. The algorithm calculates the coefficients of the TPS transformation function from the feature points. After obtaining the coefficients, transform the target skull to complete the registration. After data preprocessing, each skull model has 41,059 points, and they had the same pose and scale.

2D skull auxiliary image generation

The skull model is complex high data, which contains a

lot of redundant information. Directly feeding the whole model into the convolution neural network for training requires a large amount of computation and training time, and the design of the convolution neural network model is also very complex. In this paper, 3D skull model is transformed into 2D image and then input into convolutional neural network for skull ethnic classification. The method is inspired by the approach in Gilani *et al.* [44] and Galteri *et al.* [45].

The specific calculation process of converting the preprocessed and registered 3D skull data into 2D auxiliary image including depth, curvature and elevation information is as follows.

Calculate depth

Suppose that the 3D skull data is represented as matrix $S_{n \times 3}$:

$$S = \begin{bmatrix} x_1, y_1, z_1 \\ x_2, y_2, z_2 \\ \vdots \\ x_n, y_n, z_n \end{bmatrix} \quad (1)$$

Then each line of S is the three-dimensional coordinates of a vertex. The 2D auxiliary image is represented as $D_{m \times n}$, we need to project the skull data S to D . Suppose i is a vertex in skull data S , x_i and z_i can be transformed into 2D auxiliary image coordinates by formula:

$$a = -z_i * (m/2) + n/2 \quad (2)$$

$$b = x_i * (m/2) + n/2 \quad (3)$$

(a , b) are the coordinate values of vertex i in the image, m and n are the length and width of the image respectively. We directly take the y -axis value of each vertex as the depth value.

Calculate mean curvature

Curvature is a measure or amount of curving of the geometry. Mean curvature is the mean of any two orthogonal curvatures perpendicular to each other at a point on a surface in space. At present, there are many algorithms to solve curvature. We use the method proposed by Cohen Steiner and Morvan [46] to calculate the mean curvature. For each vertex p_i on the mesh, we take all the points in the ball with radius r_i as a geodesic neighborhood around the point p_i , and then we can define the following matrix:

$$E_{p_i}(B) = \frac{1}{|B|} \sum_{e \in B} \beta(e) \|e \cap B\| \bar{e}^T \cdot \bar{e} \quad (4)$$

where $|B|$ is the area of B , e is the edge of the mesh in B .

$\|e \cap B\|$ is the length of the mesh, always between 0 and $|e|$. $\beta(e)$ is the angle between the normal directions of two triangles with e as the common edge. We calculate the eigenvalues and eigenvectors of the matrix $E_{p_i}(B)$. The minimum eigenvalue k_{\min} and the maximum eigenvalue k_{\max} are taken as the principal curvatures k_1 and k_2 , from which the mean curvature of each vertex can be calculated:

$$k_H = \frac{k_1 + k_2}{2} \quad (5)$$

Calculate elevation

Elevation is the angle between the projection of the vector from the vertex to the origin on the XY plane and the X axis. First, the normal vector (n_x, n_y, n_z) of each vertex is calculated and transformed into spherical coordinates (n_θ, n_φ, n_r), where φ is the azimuth, θ is the elevation, and r is the radius,

$$\begin{cases} r = \sqrt{x^2 + y^2 + z^2} \\ z = r * \cos(\varphi) \\ x = r * \sin \varphi * \cos \theta \\ y = r * \sin \varphi * \sin \theta \end{cases} \quad (6)$$

The elevation angle θ can be calculated from the above formula.

Finally, the curvature value, elevation value and depth value of each vertex of 3D skull model are used as RGB channel value of 2D auxiliary image. The 2D auxiliary image of skull is shown in the Fig. 7.

Network structure of ethnic classification based on skull auxiliary image

Network structure based on skull auxiliary image is constructed for ethnic classification in this paper. Inspired by VGGNet16 [34], a 16-layer deep convolution neural network is constructed by stacking 3*3 small convolution kernels and 2*2 maximum pooling layers. Different from the previous convolutional neural network, large size kernels are not used in the network, but all 3 * 3 small kernels and 2 * 2 pooled kernels. The stacked small filter can not only keep the size of receptive field unchanged, but also reduce the number of parameters and increase the nonlinear operation, which makes the network model have stronger learning ability for features, increase the fitting expression ability of the network and improve the performance of the model. The specific network structure is shown in the Fig. 7.

It can be seen from the Fig. 8 that our network consists of 13 convolution layers (conv1-conv13) and 3 full connection layers. We input the 96 * 96 2D skull

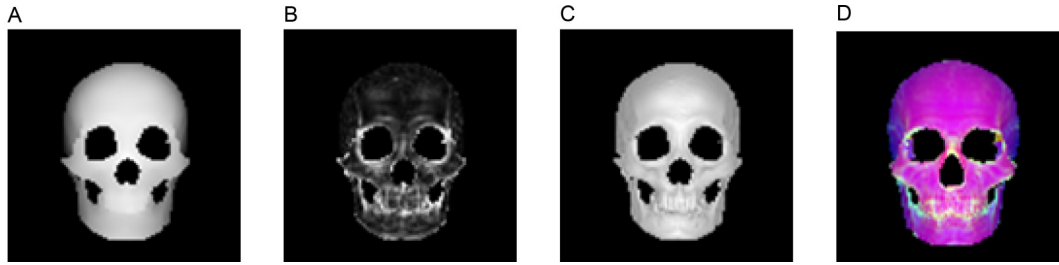


Figure 7. 2D skull auxiliary image example. (A) 2D skull depth image. (B) 2D skull curvature image. (C) 2D skull elevation image. (D) 2D skull auxiliary image containing depth, curvature and elevation.

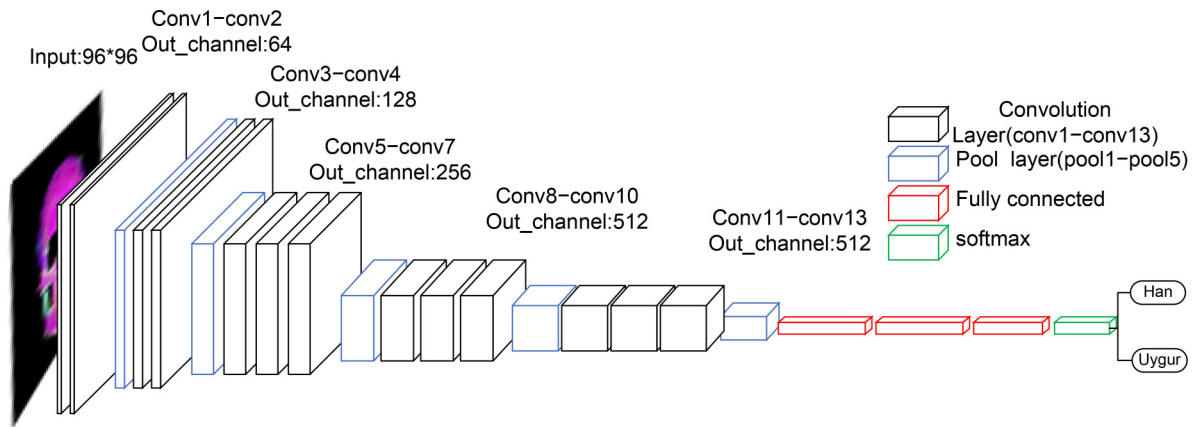


Figure 8. Network structure of ethnic classification based on skull auxiliary image.

auxiliary image into the network, and then use $3 * 3$ convolution kernel to obtain deeper and more detailed features of skull. In order to reduce the size of the feature map and improve the network anti-interference ability, the max pool layer (pool1–pool5) connects conv2, conv4, conv7, conv10 and conv13 respectively. The network ends with three full connection layers and a softmax classification layer. Finally, the input image can be divided into Han and Uyгур by softmax layer to complete the ethnic classification.

Activation function: To speed up convergence and improve the sparse representation of the neural network, all the activation functions of convolution layer use ReLU function. ReLU function is defined as

$$f(x) = \max(0, x) \quad (7)$$

Loss function: Considering the cross-entropy loss function does not depend on the partial derivative of the activation function in the process of parameter updating, it is used as the following formula in our study

$$C_0 = \frac{1}{N} \sum_{i=1}^N -[y_i \log p_i + (1 - y_i) \log (1 - p_i)] \quad (8)$$

where N is the number of samples, y_i is the label value of samples, 1 represents Han and 0 represents Uyгур, p_i is the probability that the prediction sample i is Han.

Optimization algorithm: The network uses Adam (adaptive motion estimation) optimization algorithm [47]. Adam is an adaptive optimization algorithm, which combines the gradient descent method with momentum and RMSprop (root mean square prop) algorithm to accelerate the gradient descent. Suppose that the derivative of the objective function C_0 to the parameter θ is g_t at time t . Calculating the estimation of the first moment $m_t = E(g_t)$ and the second moment $v_t = E(g_t^2)$ of the gradient, m_t and v_t are corrected: $\hat{m}_t = \frac{m_t}{1 - \beta_1^t}$, $\hat{v}_t = \frac{v_t}{1 - \beta_2^t}$, where β_1 and β_2 are the first-order moment attenuation coefficient and the second-order moment attenuation coefficient respectively, so

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t} + \varepsilon} \hat{m}_t \quad (9)$$

where η is the learning rate and ε is the minimum constant term, which is used to maintain numerical stability. Thus, Adam can design independent adaptive learning rates for different parameters to achieve more efficient training.

ACKNOWLEDGEMENTS

This work was partly supported by the National Statistical Science

Research Project (2020LY100), the National Natural Science Foundation of China (Nos. 62172247 and 61702293), the Key Research and Development Plan—Major Scientific and Technological Innovation Projects of ShanDong Province (No. 2019JZZY020101). We thank the support of Xianyang Hospital and People's Hospital of Toxon County for providing CT images.

COMPLIANCE WITH ETHICS GUIDELINES

The author Huijie Sun, Junli Zhao, Chengyuan Wang, Yi Li, Niankai Zhang and Mingquan Zhou declare that they have no conflict of interests.

Our research was approved by the Institutional Review Board (IRB) of the Image Center for Brain Research, National Key Laboratory of Cognitive Neuroscience and Learning, Beijing Normal University and was performed in accordance with the ethical standards as laid down in the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

OPEN ACCESS

This article is licensed by the CC By under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>.

REFERENCES

- Zhang, Z. B. (1985) The physical characters of Zang (Tibetan) nationality. *Acta Anthropologica Sinica* (in Chinese), 4, 250–258
- Zhang, Z. B. and Zhang, J. J. (1983) Physical characters of Zhuang nationality in Guangxi. *Acta Anthropologica Sinica* (in Chinese), 2, 250–258
- Zhang, Z. B. and Zhang, J. J. (1982) Anthropological studies on Li nationality in Hainan island. *Acta Anthropologica Sinica* (in Chinese), 1, 53–71
- Ai, Q. H., Xiao, H., Zhao, J. X., Xu, Y. H. and Sai, F. D. (1993) A survey on physical characteristics of Uigur nationality. *Acta Anthropologica Sinica* (in Chinese), 12, 63–71
- Zheng, L. B., Zhu, Q., Wang, Q. L., Li, C. S., Li, W. H., Chen, Z. L., Yang, Z. C. and Li, S. F. (1997) The physical characteristic of Hui nationality in Ningxia. *Acta Anthropologica Sinica* (in Chinese), 16, 11–21
- Zhang, X., H., Zheng, L., B., Yu, K., L., Bao, J., P., Wang, Z., B., Wu, Y., W. and Song, G., L. (2011) A study of the physical characteristics of the Han people from Shouguang in Shangdong. *Acta Anthropologica Sinica* (in Chinese), 30, 206–217
- Li, Y. L., Lu, S. H., Zheng, L. B., Li, Y. L., Li, Y. X., Guo, H., Cao, Y. and Chen, C. (2011) Physical characteristics of the Han people in Jiangxi. *Acta Anatomica Sinica* (in Chinese), 43, 132–141
- Zheng, L. B., Wu, Y. W., Zhang, X. H., Li, X., Liao, Y., Hu, Y., Wang, Z. B. and Gong, C. (2011) Physical characteristics of Han in Sichuan. *Acta Anatomica Sinica* (in Chinese), 42, 695–702
- Li, Y., Liu, S. H. and Zheng, L. B. (2013) Physical characteristics of Zhejiang Han. *Acta Anatomica Sinica* (in Chinese), 44, 707–716
- Xiao, M. (1980) National image and anatomical structure—a study on the physical features of several ethnic minorities in Northwest China. *Journal of Northwest University for Nationalities* (in Chinese), 01, 86–93
- Li, Z. J., Duan, X. D. and Wang, C. R. (2015) Cluster analysis of facial geometric features for six Chinese nationalities. *Journal of Dalian Nationalities University* (in Chinese), 17, 73–76
- Williams, B. A. and Rogers, T. (2006) Evaluating the accuracy and precision of cranial morphological traits for sex determination. *J. Forensic Sci.*, 51, 729–735
- Walker, P. L. (2008) Sexing skulls using discriminant function analysis of visually assessed traits. *Am. J. Phys. Anthropol.*, 136, 39–50
- Zhou, W. L. and Wu, X. Z. (2001) Observations of some non-metrical traits in the modern human skulls. *Acta Anthropologica Sinica* (in Chinese), 20, 42–48
- Weinberg, S. M., Putz, D. A., Mooney, M. P. and Siegel, M. I. (2005) Evaluation of non-metric variation in the crania of black and white perinates. *Forensic Sci. Int.*, 151, 177–185
- Holland, T. D. (1986) Race determination of fragmentary crania by analysis of the cranial base. *J. Forensic Sci.*, 31, 719–725
- Yaşar Işcan, M., Steyn, M. (1999) Craniometric determination of population affinity in South Africans. *Int. J. Legal. Med.* 112, 91–97
- Holliday, T. W. and Falsetti, A. B. (1999) A new method for discriminating African-American from European-American skeletons using postcranial osteometrics reflective of body shape. *J. Forensic Sci.*, 44, 926–930
- Gill, G. W., Hughes, S. S., Bennett, S. M. and Gilbert, B. M. (1988) Racial identification from the midfacial skeleton with special reference to American Indians and whites. *J. Forensic Sci.*, 33, 92–99
- Liu, Y. Y. (2016) The sex determination of Han nationality in North China by adult facial skull X-ray. *Chinese Journal of Forensic Sciences* (in Chinese), V84, 26–31
- Khaitan, T., Kabiraj, A., Ginjupally, U. and Jain, R. (2017) Cephalometric analysis for gender determination using maxillary sinus index: a novel dimension in personal identification. *Int. J. Dent.*, 2017, 7026796
- Franklin, D., Freedman, L. and Milne, N. (2005) Sexual dimorphism and discriminant function sexing in indigenous South African crania. *Homo*, 55, 213–228
- Shui, W., Y., Yin, R., C., Zhou, M., Q. and Ji, Y. (2013) Sex determination from digital skull model for the Han people in China. *Chinese Journal of Forensic Medicine* (in Chinese), 28, 19–21

24. Amores-Ampuero, A. (2017) Sexual dimorphism in base of skull. *Anthropol. Anz.*, 74, 9–14
25. Small, C., Schepartz, L., Hemingway, J. and Brits, D. (2018) Three-dimensionally derived interlandmark distances for sex estimation in intact and fragmentary crania. *Forensic Sci. Int.*, 287, 127–135
26. Maass, P. and Friedling, L. J. (2019) Morphometric analysis of the neurocranium in an adult South African cadaveric sample. *J. Forensic Sci.*, 64, 367–374
27. Luo, L., Wang, M., Tian, Y., Duan, F., Wu, Z., Zhou, M. and Rozenholc, Y. (2013) Automatic sex determination of skulls based on a statistical shape model. *Comput. Math. Methods Med.*, 2013, 251628
28. Yang, W., Liu, X. N. and Zhu, F. (2019) Automatic sex determination of skulls based on statistical shape model. *Comput. Sci.*, 46, 282–287
29. Luo, L., Chang, L., Liu, R. and Duan, F. Q. (2013) Morphological Investigations of Skulls for Sex Determination Based on Sparse Principal Component Analysis. *Chinese Conference on Biometric Recognition*, pp. 449–456. Berlin: Springer
30. Yang, W., Liu, X. N., Liu, X. L. and Zhu, L. P. (2019) Skull sex identification using improved convolution neural network and least squares method. *Acta Anthropologica Sinica (in Chinese)*, 38, 265–275
31. Yang, W., Liu, X. N., Wang, K. G., Hu, J. B., Geng, J. H. and Feng, J. (2019) Sex determination of three-dimensional skull based on improved back propagation neural network. *Comput. Math. Methods Med.*, 2019, 1–8
32. Hefner, J. T., Spradley, M. K. and Anderson, B. (2014) Ancestry assessment using random forest modeling. *J. Forensic Sci.*, 59, 583–589
33. Oakley, C., Bai, L., Liao, I. Y., Arigbabu, O. Abdullah, N. and Noor, M. H. M. (2019) A novel method for race determination of human skulls. In: *Pattern Recognition and Information Forensics (Zhang, Z., Suter, D., Tian, Y., Branzan Albu, A., Sidère, N., Jair Escalante, H. (eds.)). ICPR 2018. Lecture Notes in Computer Science*, vol 11188. Cham: Springer
34. Sun, H., J., Zhao, J., L., Zheng, X., Reziwanguli, X., Li, Y. and Zhou, M., Q. (2020) Skull ethnic identification by combining features of skull morphology with neural network. *Journal of Beijing University of Aeronautics and Astronautics (in Chinese)*, doi: [10.13700/j.bh.1001-5965.2020.0446](https://doi.org/10.13700/j.bh.1001-5965.2020.0446)
35. Simonyan, K. and Zisserman, A. (2014) Very deep convolutional networks for large-scale image recognition. *arXiv*, 1409.1556v6
36. Lecun, Y., Bottou, L., Bengio, Y. and Haffner, P. (1998) Gradient-based learning applied to document recognition. *Proc. IEEE*, 86, 2278–2324
37. Krizhevsky, A., Sutskever, I. and Hinton, G. (2012) ImageNet classification with deep convolutional neural networks. In: *Proceedings of the 25th International Conference on Neural Information Processing Systems*, pp. 1097–1105
38. He, K. M., Zhang, X. Y., Ren, S. Q. and Sun, J. (2016) Deep residual learning for image recognition. In: *2016 IEEE Conference on Computer Vision and Pattern Recognition*, pp. 770–778
39. Szegedy, C., Ioffe, S., Vanhoucke, V. and Alemi, A. (2016) Inception-v4, inception-resnet and the impact of residual connections on learning. *arXiv*, 1602.07261v2
40. Duan, F., Q., Yang, Y., C., Li, Y., Tian, Y., Lu, K., Wu, Z., K. and Zhou, M., Q. (2014) Skull identification via correlation measure between skull and face shape. *IEEE T. Inf. Foren. Sec.*, 9, 1322–1332
41. Lorensse, W. E. (1987) Marching cubes: A high resolution 3D surface construction algorithm. In: *Proceedings of the 14th annual conference on Computer graphics and interactive techniques*, pp. 163–169
42. Hu, L. Y., Duan, F. Q., Yin, B. C., Zhou, M. Q., Sun, Y. F., Wu, Z. K. and Geng, G. H. (2013) A hierarchical dense deformable model for 3D face reconstruction from skull. *Multimedia Tools Appl.*, 64, 345–364
43. Huang, R. K., Zhao, J. L., Duan, F. Q., Li, X., Liu, C. L., Deng, X. D., Pan, Z. K. and Zhou, M. Q. (2019) Automatic craniofacial registration based on radial curves. *Comput. Graph.*, 82, 264–274
44. Gilani, S. Z., Mian, A. and Eastwood, P. (2017) Deep, dense and accurate 3D face correspondence for generating population specific deformable models. *Pattern Recognit.*, 69, 238–250
45. Galteri, L., Ferrari, C., Lisanti, G., Berretti, S. and Del Bimbo, A. (2019) Deep 3D morphable model refinement via progressive growing of conditional generative adversarial networks. *Comput. Vis. Image Underst.*, 185, 31–42
46. Cohen-Steiner, D. and Morvan, J. M. (2003) Restricted delaunay triangulations and normal cycle. In: *Proceedings of the nineteenth annual symposium on Computational geometry*, pp. 3121–321
47. Kingma, D. and Ba, J. (2014) Adam: a method for stochastic optimization. *arXiv*, 1412.6980v9