Research on the Practical Classification and Privacy Protection of CT Images of Parotid Tumors based on ResNet50 Model

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Abstract. Parotid gland disease is one of the main causes of facial paralysis, and parotid gland tumor is a great threat to the life of patients. The main diagnostic way of parotid diseases is imaging examination, so it is of great significance for the rapid classification of parotid image. In conclusion, 51 CT images of parotid malignant tumors and 101 CT images of parotid pleomorphic adenomas are selected as the research data set, and an intelligent and efficient machine learning algorithm is proposed for the practical classification of parotid images. At the same time, this paper also explores the privacy protection of medical images. Based on the advantages of deep learning, such as no feature engineering, strong adaptability and easy conversion, ResNet50 model in deep learning is selected as the basic network framework to achieve the purpose of rapid classification of parotid CT images. This is the first time that ResNet50 classification algorithm is applied to the practical classification of parotid tumor CT images. The results show that the accuracy of the test set converges to 90% when the model is iterated 1000 times, which also proves that this study has certain practical significance and application value for the auxiliary diagnosis of parotid gland tumor and other head and neck tumors. Simultaneously, this paper also explores the application of desensitization strategy in CT images of parotid tumors, which improves the performance of the model and also greatly protects the privacy of patients, and has a good application prospect in medical big data.

1. Introduction
Among all the head and neck tumors, parotid gland tumors account for about 3% - 6% in the world, and there are many kinds of parotid gland tumors[1], among which benign tumors account for about 80%, and malignant lesions account for 20%[2]. Pleomorphic adenoma is the most common benign tumor of parotid gland[3]. The clinical manifestations of parotid gland malignant tumors are quite similar to those of benign tumors[4]. Preoperative diagnosis and differentiation of benign and malignant tumors is very important for the selection of surgical methods[5]. The imaging manifestations of parotid gland tumor can help medical staff to locate the tumor more accurately.
before operation[6]. At present, MRI, ultrasound and CT imaging are commonly used in parotid tumor imaging[7]. CT image of parotid gland tumor can help medical staff to more accurately determine the location of the tumor before operation[8], distinguish the nature of the tumor, distinguish whether it is benign or malignant, which can be used as a basis to help doctors formulate corresponding treatment plans, so that patients can get the best treatment in the first time[9].

With the development of imaging technology, medical imaging has become an indispensable part in the process of disease screening, early diagnosis, treatment selection and prognosis evaluation[10]. However, due to the growing number of medical images, traditional artificial classification makes doctors work time-consuming and laborious[11]. Moreover, manual image classification is not competent for large-scale image application scenarios [12], so it is an urgent need to use modern computer technology to quickly and effectively achieve automatic medical image classification [13]. In terms of image classification, Wang Heng et al. used the ResNet50 model to classify 1083 breast cancer samples with a sensitivity of 98%[14]. Nairveen Ali et al. used machine learning computer-aided diagnosis, especially deep convolution neural network ResNet50. ResNet50 model is used as the feature extractor of pca-lda model and classification model, which improves the efficiency of breast cancer diagnosis[15].

In this paper, ResNet50 classification algorithm is applied to the practical classification of parotid tumor CT image for the first time, and the classification accuracy is 90% in the case of less data, which is of historic significance for the auxiliary diagnosis of parotid tumor and other head and neck tumors. At the same time, with the development of medical big data, patient privacy protection has become particularly significant. Wang Tianyi and others proposed a privacy protection framework for personal medical data from the regulatory level, technical measures level and application implementation level[16]. In this paper, the CT images of parotid gland are desensitized. After the image classification, the same high accuracy rate as the original data classification is maintained, and the comprehensive evaluation index is improved. The results show that the re classification after desensitization of parotid images can not only protect the personal information of patients, but also improve the performance of the model. This shows that the study is of great significance in the auxiliary diagnosis of parotid gland tumors and other head and neck tumors in medical big data.

2. Experiment

2.1 Image data collection
A total of 152 images are used in this study. Among them, 51 are parotid malignant tumors and 101 are pleomorphic adenomas. Figure 1. is a sample of parotid malignant tumor and Figure 2. is a sample of parotid pleomorphic adenoma.

![Figure 1. Parotid malignant tumor](image1.png)

![Figure 2. Parotid pleomorphic adenoma](image2.png)

All the images of parotid gland tumors were collected in accordance with the medical standards,
and the data were from the People’s Hospital of Xinjiang Uygur Autonomous Region.

All the data used in this paper were scanned by GE light speed vct64 row CT scan. The scanning parameters were: tube voltage 100-120 kV, tube current 250-300 Ma, ball tube speed 0.4s/r, pitch 0.531/0.969, matrix 512 × 512, field of vision 18-24 cm, scanning layer thickness 5mm.

2.2 Experiment process

This experiment has developed a complete experimental scheme, which is mainly divided into five parts: Get picture data, Image classification using ResNet50 model, Image desensitization processing, Image classification after desensitization data image classification and Result comparison and analysis. As shown in Figure 3.

![Figure 3. Experiment flow chart](image)

In this paper, the ResNet50 model of deep learning algorithm is used to classify the data. 101 cases of parotid pleomorphic adenoma and 51 cases of parotid malignant tumor were randomly divided according to the ratio of training set: test set in 8:2 to ensure better training of the model. 122 training data sets were trained with ResNet50 model, and the remaining 30 data were used to test the classification performance of the model. ResNet50 model is a residual learning framework based on deep learning network, which has the advantages of easy optimization and low computational burden. Residuals are designed to solve degradation and gradient problems, so that the performance can be improved with the increase of network depth. ResNet50 includes a full connected layer and 49 convoluted layers. Image data is continuously convoluted by residual blocks. The number of channels of the image pixel matrix is getting deeper and deeper. After passing through the flat layer, the size of the image pixel matrix is changed into batch size × 2048. Finally, it is input into the full connection layer and output the probability of the corresponding category through the SoftMax layer. The value of super parameter in neural network has a great influence on the performance of the model. In this experiment, the learning rate is fixed at 0.001, the number of learning steps is 1000, and the sample size of one training is 10.

The leakage of basic personal information of patients may make their personal information illegally used, such as name, ID card number, mobile phone number, etc[17], which may cause serious economic losses to patients[18]. The leakage of the patient's personal history may damage the personal
image of the patient, affect people's views on him in daily life, and easily cause serious mental injury to the patient[19]. The leakage of patient's personal information and medication record may cause patients or their families to receive many sales calls of similar drugs, which may affect their daily life. In addition to the CT image of the parotid gland, the acquired data also contains the patient's information, such as name, ID, etc[20]. Although medical big data brings great convenience to patients and doctors, the leakage of patient information in medical big data will also bring a lot of harm and loss to patients[21]. Considering the harm of patients data leakage, research uses the data desensitization strategy of Beijing DSG company to encrypt and desensitize the original data, and encrypts the patient's name, gender. Figure 4 and Figure 5 are the appearance before and after desensitization.

![Figure 4. Raw Data](image1)

![Figure 5. Desensitization data](image2)

After encrypting and desensitizing the data, ResNet50 model is used to classify the processed data again. The data after desensitization is consistent with the parameters set in the experiment of image classification.

As this paper is an exploratory study, the number of data is few, and the learning effect of network model may not be optimal. In this experimental study, Accuracy, Loss, Precision, Recall and F1 value are used as the evaluation indexes of the model.

Assuming that \( N_{\text{all}} \) represents the number of all validation images, \( N_t \) represents the number of correctly classified images, and the model predicts the proportion of the correct number to the total amount, the expression of Accuracy is:

\[
\text{Accuracy} = \frac{N_t}{N_{\text{all}}} \tag{1}
\]

The higher the Accuracy, the closer the prediction of the training model to the real situation, the better the performance of the model. In consideration of the severity of the consequences of missed screening for patients with malignant tumors, this paper will also select Loss, Precision, Recall and F1 value to evaluate the performance of the model. We assume that:

- TP is the number of parotid pleomorphic adenomas predicted to be parotid pleomorphic adenomas;
- FN is the number of parotid malignant tumors predicted by pleomorphic adenomas;
- FP is the number of parotid malignant tumors predicted as pleomorphic adenomas;
- TN is the number of parotid malignant tumors predicted as parotid malignant tumors;

The Precision rate is to solve the proportion of positive categories in the samples identified as positive categories. Then the expression of precision is:
Recall rate is the proportion that is correctly identified as a positive category in all positive category samples. The expression of recall rate $\text{Recall}$ is:

$$\text{Recall} = \frac{TP}{TP + FN}$$  \hspace{1cm} (3)

F1 value is the harmonic mean value of precision rate and recall rate, then the expression of F1 value is:

$$\text{F1 value} = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$  \hspace{1cm} (4)

When F1 value is high, the effect of the model or algorithm is better.

3. Experimental results and comparative analysis

Finally, all the parameter results obtained from the two data experiments are shown in Figure 6:

![Figure 6. Comparison of experimental results of two groups of data](image)

In this experiment, the data of the model is less, and there is no data enhancement and expansion. It has high performance in a few datasets, which shows that the features extracted from the algorithm model in the process of classification and recognition of parotid tumor pathological images are distinctive, have higher recognition rate, and have better generalization.

Compared with the experimental results, the accuracy of image classification of the raw data and the desensitized data is the same, which shows that desensitization does not reduce the accuracy of image classification. The results show that the test loss of the desensitization data operation model is
much smaller than that of the original data, which shows that the classifier works better in modelling the relationship between the input data and the output target, and the model accuracy is higher. F1 value synthesizes the results of precision rate and recall rate, which can better evaluate the quality of classification model or algorithm. As shown in the figure, the F1 value of the desensitized data is slightly higher than that of the original data. We conclude that desensitization of patient information in CT images will not affect the accuracy of tumor identification, reduce the loss of model testing, and protect the patient’s personal information.

4. Conclusion
In this paper, ResNet50 model, which has the advantages of simple feature extraction and high precision compared with traditional machine learning, is adopted. This model also shows better classification performance in the case of less data sets. At the same time, the CT image of parotid gland was desensitized. The desensitized data still showed a good classification accuracy with the model, which reduced the test loss of the model and improved the classification performance of the model. Moreover, desensitization of patients’ CT images can also protect patients’ personal information and sensitive information, and better protect patients’ personal interests. With the development of medical big data and the growth of medical image data, the deep network automatic classification method based on ResNet50 model will play a development potential. In the near future, we will continue to carry out relevant research, test with more comprehensive data sets, further improve the speed and accuracy of model classification, and continuously improve the application value of this method in the near future.

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Reference
[1] Wei Y, Xiao J, Pui M H, et al. Tuberculosis of the parotid gland: computed tomographic findings[J]. Acta Radiologica, 2008, 49(4): 458-461.
[2] Jia Y L, Bishwo S P, Nie X, et al. Synchronous bilateral multifocal acinic cell carcinoma of parotid gland: case report and review of the literature[J]. Journal of Oral and Maxillofacial Surgery, 2012, 70(10): e574-e580.
[3] Wang S, Shi H, Wang L, et al. Myoepithelioma of the parotid gland: CT imaging findings[J]. American Journal of Neuroradiology, 2008, 29(7): 1372-1375.
[4] Gibson T C, Bishop J A, Thompson L D R. Parotid gland nodular fasciitis: a clinicopathologic series of 12 cases with a review of 18 cases from the literature[J]. Head and neck pathology, 2015, 9(3): 334-344.
[5] Zhan K Y, Khaja S F, Flack A B, et al. Benign parotid tumors[J]. Otolaryngologic Clinics of North America, 2016, 49(2): 327-342.
[6] Iko B O, Chinwuba C E, Myers E M, et al. Sarcoidosis of the parotid gland[J]. The British journal of radiology, 1986, 59(702): 547-552.
[7] Quer M, Vander Poorten V, Takes R P, et al. Surgical options in benign parotid tumors: a proposal for classification[J]. European Archives of Oto-Rhino-Laryngology, 2017, 274(11): 3825-3836.
[8] Dong Y, Lei G W, Wang S W, et al. Diagnostic value of CT perfusion imaging for parotid neoplasms[J]. Dentomaxillofacial Radiology, 2014, 43(1): 20130237.
[9] Zerpa V Z, Gonzáles M T C, Porras G A, et al. Diagnostic accuracy of fine needle aspiration cytology in parotid tumours[J]. Acta Otorrinolaringologica (English Edition), 2014, 65(3): 157-161.
[10] Abendroth C S, Frauenhoffer E E. Nodular fasciitis of the parotid gland. Report of a case with
presentation in an unusual location and cytologic differential diagnosis[J]. Acta cyto
logica, 1995, 39(3): 530-534.
[11] Li Q, Cai W, Wang X, et al. Medical image classification with convolutional neural
network[C]//2014 13th international conference on control automation robotics & vision
(ICARCV). IEEE, 2014: 844-848.
[12] Kumar A, Kim J, Lyndon D, et al. An ensemble of fine-tuned convolutional neural networks for medical image classification[J]. IEEE journal of biomedical and health informatics, 2016, 21(1): 31-40.
[13] Rezaeilouyeh H, Mollahosseini A, Mahoor M H. Microscopic medical image classification framework via deep learning and shearlet transform[J]. Journal of Medical Imaging, 2016, 3(4): 044501.
[14] Wang Heng, Li Xia, Liu Xiaofang, Xu Wenlong. Breast cancer pathological image classification based on ResNet50 network [J]. Journal of China University of metrology, 2019,30 (01): 72-77
[15] Nairveen Ali,Elsie Quansah,Katarina Köhler,Tobias Meyer,Michael Schmitt,Jürgen Popp,Axel Niendorf,Thomas Bocklitz. Automatic label-free detection of breast cancer using nonlinear multimodal imaging and the convolutional neural network ResNet50[J]. Translational Biophotonics,2019,1(1-2).
[16] Zhang D. Big data security and privacy protection[C]//8th International Conference on Management and Computer Science (ICMCS 2018). Atlantis Press, 2018.
[17] Cuzzocrea A. Privacy and security of big data: current challenges and future research perspectives[C]//Proceedings of the first international workshop on privacy and security of big data. 2014: 45-47.
[18] Price W N, Cohen I G. Privacy in the age of medical big data[J]. Nature medicine, 2019, 25(1): 37-43.
[19] Yang Y, Zheng X, Guo W, et al. Privacy-preserving fusion of IoT and big data for e-
health[J]. Future Generation Computer Systems, 2018, 86: 1437-1455.
[20] Costa F F. Big data in biomedicine[J]. Drug discovery today, 2014, 19(4): 433-440.
[21] Wang Tianyi, Liu Aiping. Research on privacy protection of medical data in big data environment [J]. Information technology and network security, 2019,38 (08): 28-32