Skin Lesion Classification based on Deep Convolutional Neural Network

Youteng Wu
Computer Science and Technology College
Inner Mongolia Minzu University
Tongliao, China
1214265747@qq.com

Agyenta Charity Lariba
Computer Science and Technology College
Inner Mongolia Minzu University
Tongliao, China
AgyentaCharity2016@gmail.com

Haotian Chen
Yunnan Institute of Nationalities
Yunnan Minzu University
Kunming, China
cloudchen1998@outlook.com

Haiyan Zhao*
Computer Science and Technology College
Inner Mongolia Minzu University
Tongliao, China
zhaohaiyan@imun.edu.cn

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***Abstract*—Skin cancer is one of the most common cancers, and its early detection has a huge impact on its outcomes. In this paper, the deep convolutional neural network is improved with the idea of transfer learning to classify 7 types of skin lesions that are from ISIC 2017 HAM10000 dataset. First, the skin lesion images are trained with a 3-layer convolutional neural network after preprocessing. Then for InceptionV3, ResNet50 and DenseNet201, remove the output layer of each original network, add new pooling layer and full connection layers to different networks respectively. After that, combine some of the convolution layers and pooling layers with the new pooling and full connection layers to form three new improved models, based on the original deep conventional networks. Finally, the training parameters which are from ImageNet network are fine-tuned on new improved InceptionV3, ResNet50 and DenseNet201 to finish the classification. The experimental images' size is 224*224, and the experiments turn out that three improved networks get better results, and the improved ResNet50 gets the best which accuracy is 86.69%. Its accuracy is 3% higher than the comparable other methods.**

Keywords*—*deep convolutional neural network, image processing, skin lesion images, transfer learning

I. INTRODUCTION

Skin lesion is a disease caused by alterations in the characteristics of normal skin cells, and skin cancer is one of the skin lesions. The number of skin lesions cases is increasing with the years, and the exposure of the skin to the sun's rays is one of the main causes. Take Indonesia as an example, skin cancer accounts for 5.9% to 7.8% of all types of cancers every year[1]. The World Health Organization reports that there are approximately 3 million new non-melanoma and 132,000 new melanoma cases which are diagnosed worldwide annually[2]. Medical imaging technology is the instrumentals in diagnosing cancer, and dermoscopy is an equipment that skin lesions can be shown and diagnosed with high-resolution Image-based techniques[3]. Dermoscopy can improve the success rate of diagnosing melanoma and non-melanoma skin cancers, and diagnosis based on dermoscopic photographs is more accurate[4]. Although being specialized training with the skin Microscopic analysis, dermatologists still lead to 21% of misdiagnoses because of some human factors such as fatigue and mental state[5]. So computer-aided systems with high classification accuracy will help identify skin lesions objectively, quickly, and reliably.

Today, both advances in artificial intelligence technology and successful research in the field of computer vision have led to a paradigm shift in healthcare fields[6]. How to classify skin lesion cases with artificial intelligence is a challenge, the classification of skin lesions is of great significance in early diagnosis of skin diseases.

II. RELATED WORK

A. Research Methods in Skin Lesions Classification

Due to many deaths as a result of skin cancer, many researchers all over the world have joined in the research on skin cancer classification and diagnoses. With continuous researches of many researchers, the papers on skin cancer are increasing, and the renewal and upgrading of skin cancer classification and diagnoses materials are automatically promoted. Fatima et al.[7] used a computer-assisted six-step method to detect melanomas by statistically analyzing 21 predetermined parameters of skin Cancer. Qian et al.[8] used a two-stage method to identify the lesion's location first and then classify. They asserted that this two-stage classification method was superior to a single-stage classification. Ercal et al.[9] used artificial neural networks to discriminate malignant melanomas from three different benign tumors with comparable features successfully, and they advocated the use of fuzzy logic and hierarchical neural networks to classify skin lesions in another study. Binder et al. [10] examined what had done by the computer-aided systems and human specialists to determine the usefulness of artificial neural networks in dermoscopy image processing. They found the human specialists achieved 75% accuracy, while the artificial neural network achieved 78% accuracy.

B. Deep Learning Research in Skin Lesions Classification

Deep learning has been used to detect malignant tumors in the field of skin cancer diagnosis. Several organisms are used in these approaches to classify skin cancers, such as conventional neural network and others, in order to obtain an accurate diagnosis of skin cancers [11]. Mishra et al. [12] compared skin lesion image segmentation algorithm based on a variety of melanoma detection. Pomponiu et al. [13] proposed a pre-trained deep neural network which is used to automatically extract typical features, and then the method is used to identify malignant skin lesions based on the prediction. The classification performance of training method is superior to other methods. Lopez et al. [14] constructed a model for skin disease recognition based on VGGNet network. During the training process, the corresponding parameters were fine-tuned, and the test accuracy of skin disease image data set was up to 81.33%. Guan Qiu et al. [15] extracted dermatologic images by constructing deep residual network with high dimensional features, residual learning is used to prevent network gradient degradation and reduce the difficulty of network training to achieve melanoma valid identification. Li Hang et al. [16] used pre-trained RES-152 models to extract images of skin lesions first, and then train these features with Support Vector Machine, and finally achieved 86.28% accuracy in the binary classification task. Hexueying et al.[17] used transfer learning to train network parameters and data enhancement technology to amplify data volume, and their recognition rate reached 71.34% based on VGG19. YU Jusong[18] uses VGGNet-19, Inception-V3 and ResNet-50 network models based on transfer learning to classify and predict skin disease images. In these three models, the ResNet-50 model has the best classification effect and the accuracy is 83.26%.

III. THEORICAL BACKGROUND

Deep learning is a machine learning technique that has made great use of human being's knowledge, statistics, and applied mathematics in the past few years[11]. Deep learning is good at quickly learning from images in a fast way, learning patterns and colors, and continuing to teach yourself based on what you've learned to improve performance. Deep learning can train and learn computers through structures such as convolutional neural network(CNN).

A. Brief Introduction of Convolutional Neural Network

CNN is an advanced neural network composed of multiple layers of regularized neural networks and is considered to be a class of feedforward neural networks, mainly used in image classification. The structure of CNNs is as follow:

1) Input Layer: The main work of this layer is the input of original image data, which is input in the mode of the image matrix, and data preprocessing is usually performed before input.

2) Convolutional Layer: The convolutional layer is the basic component of the CNN architecture, which is usually composed of linear operations for feature extraction. A small number of array called a kernel is applied to the entire input.

3) Pooling Layer: The pooling layer is also known as the down-sampling layer. Its main purpose is to reduce the computation time while avoiding over-training the network.

4) Fully Connected Layer: It is the final stage of CNN, connecting all layers together and participating in the transition to the classification stage.

5) Output Layer: realize the final classification task.

B. Transfer Learning

Transfer learning refers to the use of the original to solve tasks such as network structure, weights and training method to get better results. The reason why transfer learning can be applied is that the features of convolutional neural network in shallow learning are universal. In case of insufficient samples, you can use transfer learning, to transfer general feature learning from other trained networks, to save training time and get better recognition results. The main idea of transfer learning is to use the knowledge of source domain to learn about the target domain as Fig.1.

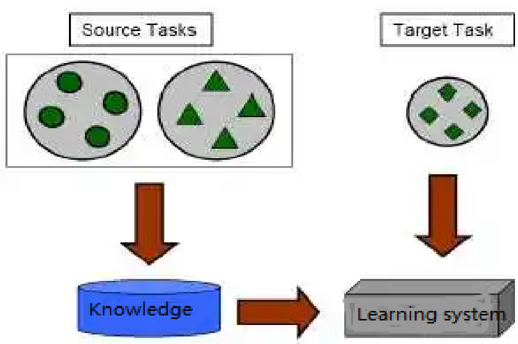

Fig. 1. Learning process of transfer learning

IV. EXPERIMENTAL DESIGN

A. Data Preprocessing

Before carrying out this experiment, some digital image processing techniques were used to preprocess the skin lesion images, which are shown below.

1) Image Cropping: The size of the original image itself is 600*450. However, the edge does not contain useful information. Therefore for optimal detection results, that part is cropped out. In Fig.2, the left is the original image and the right is the 224*224 image where the edge is croped out.

Fig. 2. The original image and the cropped image

2) Removal of Hair: After cropping, it is observed that there are some interference signals such as hair in most of the images. The closing operation in mathematical morphology is used to remove the hair. And grey processing, binarization processing, and other techniques also assist. Fig.3 shows the hair removal effect of a RGB image. Among it, the left top is the original image, the right top is the result of binarization, the left bottom is the result of removing little noises and the right bottom is the image that has been processed.

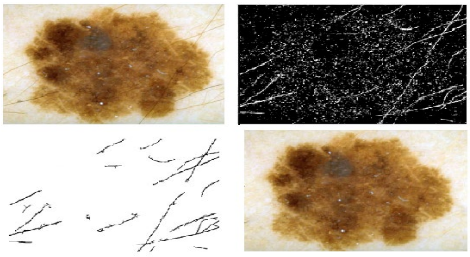

Fig. 3. The effect of hair removal

B. Experimental Data Design

The experiments are carried out under Anaconda 3, based on TensorFlow and Keras deep learning framework. Experiments were performed on an Intel core i9 9820X processor with 64GB RAM. We are using TensorFlow to program. The experimental dataset comes from the public dataset ISIC 2017 HAM10000, which covers 10015 image data from 7 kinds of skin lesions, covering the face, back and other positions. The skin disease dataset includes 7 categories of all important diagnostic categories in the field of pigmented lesions: melanocytic nevi, melanoma, benign keratosis lesions, basal cell carcinoma, actinic keratosis and intraepithelial carcinoma, vascular lesions and dermatofibroma.

1) Amplification of Experimental Data: Various types of skin lesion images have unbalanced samples. Unbalanced samples will make the learning process unable to estimate the overall samples unbiased, which may reduce the model's predictive ability. The consequence of malignant skin diseases is very serious, so we would rather classify benign lesions as malignant and then perform manual screening than classify malignant as benign.

After preprocessing, the following processing is mainly performed to augment the image data.

a)Decreasing: For the pigmented nevus with the largest sample size, the number of images participating in the training is under-sampled by random sampling, and the reduction ratio is 0.15.

b) Increasing: For the categories with few samples, such as dermatofibroma and vascular lesions, the oversampling idea is applied to randomly crop, flip, and translate, and the preprocessed images obtain new image samples that are 8 times the original image data.

c) Remain unchanged: No increase or decrease was made to the data with a sample size of about 1000.

The balance of the dataset after the above processing is shown in Table I. The distribution of various samples after the dataset is sampled.

TABLE I. DISTRIBUTION OF VARIOUS SAMPLES AFTER DATA SET SAMPLING

	Number of samples	**Adjustment coefficient**	**Adjusted sample Size**
Pigmented Nevus	6707	0.15	1006
Melanoma	1113	1	1113
Benign Keratosis	1099	1	1099
Basal Carcinoma	514	2	1028
Actinic Keratosis	327	3	981
Vascular disease	142	8	1136
Dermatofibroma	115	8	920

2) Data Set Partitioning: For the skin lesion images from HAM10000, a total of 7283 samples were selected for classification after preprocessing and amplification or reduction. 80% samples were chosen as the training set, while the rest were the test set.

C. The Design of Deep Convolutional Network Based on Transfer Learning

*1) The design of basic convolutional network:*To verify the fisibility of this question, we design a CNN network with three layers. In this network, there is a input layer, three pairs of convolutional layer and max pooling layers, and two fully connections layers as the end. The detail is shown in Fig.4.

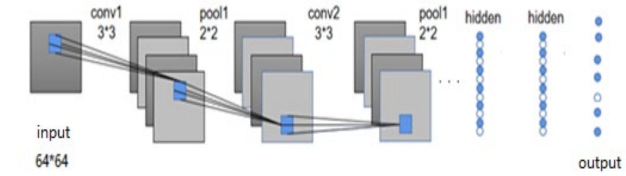

Fig. 4. The structure of CNN

*2) The disign of deep convolutional network:*To improve the accuracy and training speed, InceptionV3, ResNet50 and DenseNet201 with ImageNet trained weight were transfered to train the models on total preporcessed 7283 skin leision samples. Take ResNet50 as an example, the revised network as Fig.5.

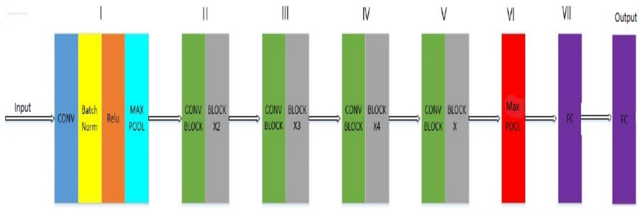

Fig. 5. The structure of improved ResNet50

The main steps of training with improved networks are as follows:

a) Load the ImageNet parameter.

b)Construct a new model: Freeze part of the convolutional layers in the improved deep convolutional network, select the remaining convolutional layers and the newly added pooling layer and full connection layer to form a new model to be trained.

c) Real-time generation of batch enhanced data for feature extraction. In this process, image enhancement is mainly carried out by random flipping, random horizontal and vertical offset amplitude, shearing and amplification.

d) Start training. Data are sent to the new model to be *trained* in batches. During the training, the monitored value of each network model is test accuracy. Take Adam as the training optimizer. Cycle times are 30, batch size is 64, the loss function is cross entropy function, activation *function* is ReLU, and the classification function is Softmax. And the initial learning rate is set to 0.001, the ReduceLROnPlateau function and EarlyStopping function in Keras are used to reduce the learning rate during training.

e) Repeat c) ~ d) to fine-tune the parameters.

V. Analysis of Results

A. The result of 3-layer convolutional neural network

To test the 3-layer convolutional neural network, we trained 64*64 color images that aren't preprocessed. The accuracy is shown in Fig.6, and the change of loss function is shown in Fig.7.

In Fig.6 and Fig.7, blue line represents the training set's accuracy and loss function changes, and yellow line represents the training accuracy and loss on the validation set. As can be seen from the results in Fig.6, the training accuracy reaches 78.38% and the validation accuracy reaches 75.32%, and both of them show a gradual upward trend with the change of the number of cycles. In Fig.7, the loss functions' change for training and validation of 64*64 images shows a gradually decreasing trend. So, these results show that the network is suitable to classify the images.

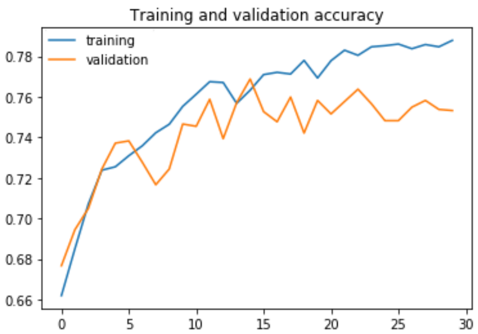

Fig. 6. Accuracy for training and validation of 64*64 images

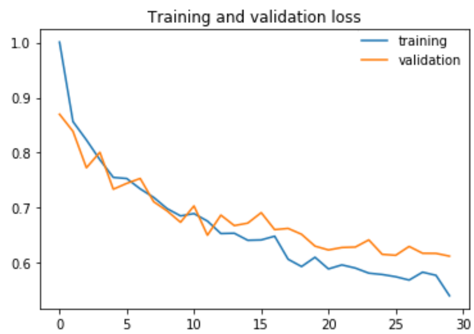

Fig. 7. Loss function for training and validation of 64*64 images

B. The result of improved network

TABLE II. Comparison of Classification Results of Different Deep Conventional Network

	InceptionV3	ResNet50	DenseNet201
Training accuracy	98.0%	97.94%	99.12%
Validation accuracy	85.80%	86.69%	86.91%
Training loss	0.0780	0.0745	0.0278
Validation loss	0.6036	0.5673	0.6267

Table II shows a comparison of classification results of improved different deep conventional network based on transfer learning. The preprocessed images are trained based on the above-mentioned deep conventional structure.

TABLE III. Comparison of Classification Results of Different Papers

	Network	Categories	accuracy
Reference 14	VGGNet	2	78.66%
Reference 16	Res-152+SVM	2	86.28%
Reference 17	VGG19	3	71.34%
Reference18	VGGNet-19	7	81.93%
Reference18	Inception-V3	7	81.01%
Reference18	ResNet-50	7	83.26%
This paper	InceptionV3	7	85.80%
This paper	ResNet50	7	86.69%
This paper	DenseNet201	7	86.91%

Table III shows the comparison results between other papers and ours. In 3rd column, categories mean how many kinds of skin lesions have been classified. It can be seen from Table III that after training the preprocessed images, the various skin disease's classification accuracy has been significantly improved based on our improved networks. After comparing both accuracy and loss function of different deep conventional networks in Table II, ResNet50's accuracy reaches 86.69% while the loss function of validation is 0.5673, so it is the best and will be studied in the future further.

VI. Conclusion

In recent years, the incidence of skin diseases has become higher and higher, so the research on the classification of skin cancer is of great significance for the auxiliary diagnosis of skin cancer. This paper mainly explored the classification of skin lesion images with HAM10000. According to transfer learning idea, three new models which are based on InceptionV3, ResNet50 and DenseNet201 network are constructed. A few convolutional layers, the newly added pooling layer and fully connected layer were selected to fine-tune the parameters of the new models separately. The experimental results show that improved ResNet50 is the best.

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