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Skin Lesion Classification Based on Convolutional Neural Network

Agyenta Charity Lariba[1,2*], Mathias Justice Akanzawon[2]

[1]*Department of Computer Science and Technology College, Inner Mongolia University for the Nationalities, Tongliao, China*
[2]*Catholic University College of Ghana, Fiapre, sunyani-Ghana, agyentacharity2016@gmail.com*
Corresponding Author: Agyenta Charity Lariba, agyentacharity2016@gmail.com

Abstract

Skin cancer is one of the most common cancers, and its early detection can have a huge impact on its outcomes. Deep learning, especially convolutional neural networks, performs well in processing massive amounts of data, especially image data in classifying skin cancer. In this paper, convolutional neural networks are mainly used to diagnose and classify 7 types of skin lesions, including melanoma, basal cell carcinoma, melanocytic nevus, actinic keratosis, intraepithelial carcinoma, benign keratinoid lesions, dermatofibroma, and vascular lesions. First, the characteristics of skin lesion images are analyzed, using image processing technology and sampling technology to preprocess skin lesion images. Then the training parameters of imageNet network are adjusted through the idea of transfer learning on InceptionV3, ResNet50, DenseNet201, and other networks to perform training classification. Furthermore, different convolutional neural network models are built for classification. In order to validate the classification performance of various convolutional neural network models, this paper adopts ISIC 2017 HAM10000 dataset for experiments. The experimental results show that proper preprocessing is necessary when applying CNN for image classification. In classifying the 224*224 skin lesion images, the classical deep convolutional network with DenseNet201 achieved a remarkable performance classification accuracy of 99.12% for training and 86.91% for testing.

Keywords: *convolutional neural network, image processing, skin cancer, skin lesion images, deep convolutional neural network*

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I. INTRODUCTION

Cancer is the leading cause of death in many countries around the world and an unfortunate barrier to increasing life expectancy [1]. Cancer is ranked among the top causes of death before the age of 70 worldwide [2]. Skin cancer is a disease caused by alterations in the properties of normal skin cells. Skin cancer is a malignant cancer that is common in Asia. A case in point is Indonesia, where in addition to cervical cancer and breast cancer, it accounts for 5. 9% to 7. 8% of all types of skin cancer every year [3]. The World Health Organization reports that annually, approximately 3 million new non-melanoma and 132,000 new melanoma cases are diagnosed worldwide[4] The number of cases is increasing year by year, and one of the main reasons for the increase is the exposure of the skin to the sun's rays. Because of the few specialists in this sector, developing new rapid and accurate diagnosis methods is crucial in combating these cancers [5]. Medical imaging is instrumental in diagnosing cancer, where dermoscopy is a method of showing skin lesions with high-resolution Image-based techniques for diagnosing skin lesion [6]. Dermoscopy can improve the success rate of diagnosing melanoma and non-melanoma skin cancers, and diagnosis based on dermoscopic photographs is more accurate [7]. Although it is a specialized training and skin Microscopic analysis, dermatologists still lead to 21% of misdiagnoses due to human factors such as fatigue and mental state[8] Computer-aided systems help to objectively, rapidly and reliably identify skin lesions, as well as various other fields.

Today, advances in artificial intelligence technology and successful research in the field of computer vision have led to a paradigm shift in healthcare [9]. Skin cancer is a challenge, particularly in estimating incidence rates, for several reasons. First, there are many types of skin cancers, and challenges can arise when collating the data. For example, non-melanoma skin cancers are often not tracked by cancer registries, or registries for such cancers are often incomplete because most cases are successfully treated with surgery or ablation[10]. Secondly, many cancer cases are not identified or recorded. Some countries have no cancer registries, some regions have few records, and those countries that have suffered war or other destruction have incomplete records. And some cancer patients do not consult a doctor [11]. Finally, clinical diagnosis is inherently subjective and complex, and its accuracy largely depends on the dermatologist's experience, which is believed to be between 75% and 85% [12]. Manual intervention is highly subjective and rarely repeated. Because of these factors, reported global skin cancer incidence rates are likely to be underestimated. Non-melanoma skin cancers are also often ignored in comparative rankings of the most common cancers[13]. Therefore, the classification of skin cancer is of great significance in improving diagnostic accuracy.

II. Literature Review

Due to many deaths of people as a result of skin cancer, many researchers all over the world have joined in the research on skin cancer classification and diagnoses. The theoretical literature on skin cancer is increasing, which automatically promotes the renewal and upgrading of skin cancer classification and diagnosis materials with the continuous development of science and technology. Skin cancer spectrum is gradually optimized from the initial single frequency imaging and aims at the problem of classification.

Fatima et al.[14] used a computer-assisted six-step method to detect melanomas by statistically analyzing 21 pre-determined parameters of skin Cancer. Qian et al. [15] used a two-stage method to first identify the lesion's location and then classify it. They asserted that this two-stage classification method was superior to a single-stage classification. Ercal et al [16] used artificial neural networks to successfully discriminate malignant melanomas from three different benign tumors with comparable features, and they advocated the use of fuzzy logic and hierarchical neural networks to classify skin lesions.

AlmarazDamianet al [17] using handcrafted features achieved 92% success in classifying benign and malignant skin lesions with linear regression and SVM. Binder et al.[18] examined the classification success of computer-aided systems and human specialists to determine the usefulness of artificial neural networks in Dermoscopy image processing. Human specialists achieved 75% accuracy in their investigation, while the artificial neural network achieved 78% accuracy. Mahbod et al. [19] proposed a CNN model that classifies melanoma with 87% accuracy sampling over 600 lesion images. In another study, Kawahara et al.[20] achieved 81% success in classifying 1300 skin lesion images taken with a non-Malignant skin lesions Neural Computing and Applications 123 dermoscopic camera.

Kavitha and Suruliandi [21] extracted texture and color features from a dataset of 150 dermoscopic images and then classified melanoma and non-melanoma lesions with 88% accuracy using SVM. Similarly, Zhang et al. [22] achieved 85% accuracy in melanoma classification using the ARLCNN50 model. And Bi et al. [23] achieved 74% accuracy with a hyper-connected CNN model to classify a dataset consisting of 1011 skin lesion images.

Convolutional Neural Networks (CNNs), are a type of deep learning approach, which has been widely used in medical image processing in recent years, in the field of skin cancer diagnosis.

Knowledge of skin cancer classification

The incidence of skin cancer is increasing worldwide due to prolonged exposure to sunlight, climate change, and personal and social conditions[23]. Overall, skin cancers include cutaneous melanoma (CM) and non-melanoma skin cancers (NMSC), mainly represented by basal cell carcinoma (BCC) and squamous cell carcinoma (SCC). Merkel cell carcinoma (MCC) is a special type of skin cancer that has historically been classified as a neuroendocrine tumor.

III. Methodology

This paper mainly studied the experimental classification of skin lesion data by using the deep transfer learning method. The research contents are as follows:

(1) firstly, the published dermatology data set HAM10000 is analyzed and preprocessed. Then, a three-layer basic convolution neural network model is constructed to classify seven skin lesion images. The classified image sizes were 28*28, 64*64, 224*224, unprocessed, and preprocessed respectively. The preprocessing was carried out to clean the data for enhanced classification accuracy, and the experimental results show that the classification effect of the pre-processed images is slightly better than that of unprocessed images.

(2), Based on the pre-processed 224*224 image data, the corresponding Inception network, ResNet network, and DenseNet network are improved by using the transfer learning idea, and some levels of the improved model are selected to fine-tune the parameters, so as to construct different network models for optimum classification of the dermatosis images. The classification results show that with the increase in network depth, the classification effect is significantly improved, and the improved ResNet50 network model obtained the best classification effect.

(3) On the improved ResNet50 network, the category weight and SE block methods are adopted respectively, and all levels of parameters of the whole model are selected for training and fine-tuning to improve the classification results of the pre-processed 224*224 images. Meanwhile, the classification effect of the other two methods(Inception network and DenseNet network) is better in some ranges than that of the improved ResNet50 network. Before carrying out the experiment, some digital image processing techniques were used to prepare the skin lesion images, as shown below.

Image cropping

The size of the original image itself is 600*450. However, the edges do not contain useful information. Therefore for optimal detection results, those parts are cropped out, and the pixels of the images are increased. Fig.1. (a) shows the original image, (b) is the 299*299 image, and (c) is the 224*224 image accordingly.

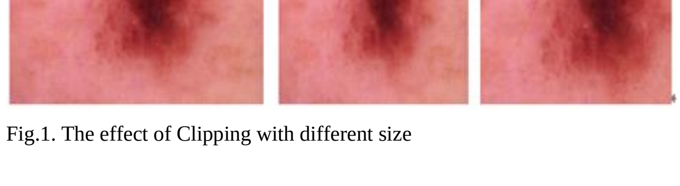

Fig.1. The effect of Clipping with different size

Color space transformation

Color space transformation is generally divided into RGB color space. The skin disease image is exhibited as a color image based on the RGB color space. The values of the three components of R, G, and B in the RGB color space describe the brightness values of red, green, and blue, respectively. It is represented by a tuple matrix. Usually, each value of the triple is between 0 and 255.

Fig. 2 shows the effect of decomposing a skin lesion image into three grayscale images; red, green, and blue.

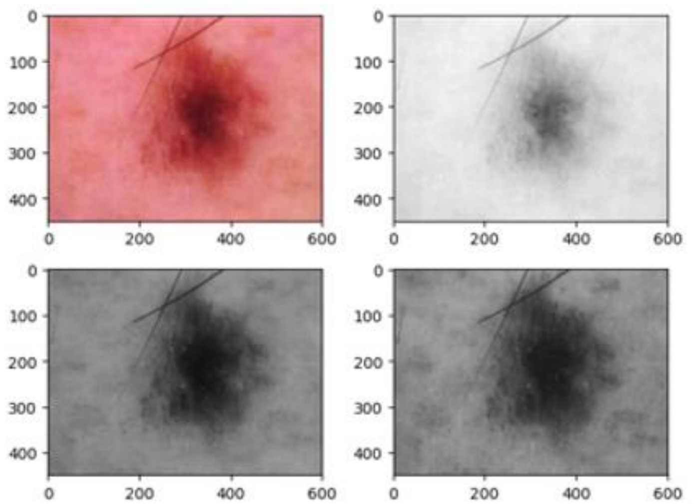

Fig.2. RGB image and gray image of R, G, and B channels

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, assisted by degree stretching, and histogram techniques. Fig.3**.** shows RGB images of the hair removal effect.

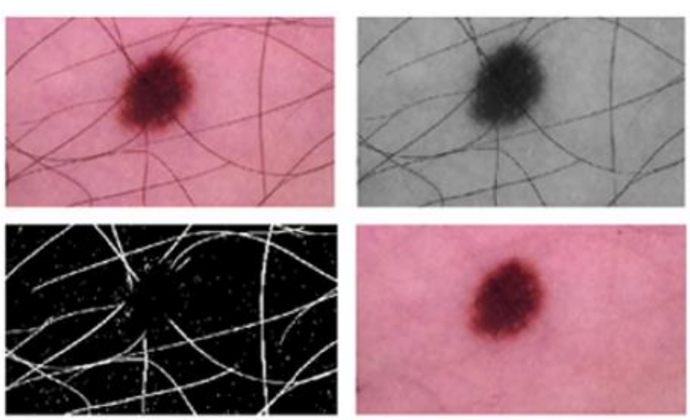

Fig. 3. RGB images of hair removal effect

Experimental environment and data

The experiments are carried out under Anaconda 3, based on TensorFlow and Keras deep learning framework. The experimental dataset is from the public dataset I SIC 2017 H AM10000, which covers 10015 image data from 7 kinds of skin lesion, covering the face, back, and other positions[25].

Amplification of experimental data

Various types of skin cancer 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. Benign lesions are costly. So we rather classify benign lesions as malignant and then perform manual screening rather than classify malignant as benign.

The image size from HAM10000 is 600*450. After preprocessing, the following processing is mainly performed to augment the image data [26].

i. 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.

ii. 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 4 to 5 times the original image data.

iii. No increase or decrease was made to the data with a sample size of about 10000.

The balance of the dataset after the above processing is shown in Table 1. The distribution of various samples after the dataset is sampled

TABLE 1. DISTRIBUTION OF VARIOUS SAMPLES AFTER DATA SET SAMPLING

	Shorthand	**Number of samples**	**Adjustment coefficient**	**Adjusted sample Size**
Pigmented Nevus	MV	6707	0.15	1006
Melanoma	MEL	1113	1	1113
Benign Keratosis	BKL	1099	1	1099
Basal Carcinoma	BCC	514	2	1028
Actinic Keratosis	AKIEC	327	3	981
Vascular disease	VASC	142	8	1136

Data set preparation

For the skin lesion images from HAM10000, a total of 7283 samples were selected for classification after preprocessing and amplification or reduction. The division of training and testing datasets is shown in Table 2.

TABLE 2. DATA DIVISION

Types of skin lesions	MV	MEL	BKL	BCC	AKIEC	VASC	DF
Total number of samples	1006	1113	1099	1028	981	1136	920
Number of training samples	805	890	879	822	785	909	736
Number of test samples	201	223	220	206	196	227	184

Since the training of artificial neural networks for automatic diagnosis of pigmented skin lesions is hindered by the small number and lack of diversity of dermoscopy image datasets, this study uses HAM10000 of ISIC2017 as the dataset. The dataset contains 10015 images of multi-source dermoscopic pigmented lesion images as a training set. Dermoscopy images of different populations are collected in this dataset and stored differently. The metadata file of this dataset contains dermatological image numbers, the index value corresponding to the file path of the lesion image, the type of diagnosis, the age, and gender of the patient, the location of the lesion, and so on.

The skin disease dataset includes 7 categories of all-important diagnostic categories in the field of pigmented lesions: actinic keratosis and intraepithelial carcinoma/Bowen disease (akic), basal cell carcinoma (bcc), benign keratinoid lesions (solar rash) / seborrheic keratosis and lichen planus keratosis (lpk), dermatofibroma (df), melanoma (mel), melanocytic nevi (mn) and vascular lesions (hemangioma, angiokeratoma, pyogenic granulomas and hemorrhages, vascular lesions). More than 50% of the lesions in these images were confirmed by histopathology, and the remaining cases were also confirmed by follow-up examinations, expert consensus, or in vivo confocal microscopy. Dataset lesion contains multiple images that can be tracked by the lesionid column in the HAM10000metadata file. Also available in the CSV file provided with the dataset.

IV. ANALYSIS OF RESULTS

In the case of 3-layer convolutional neural network depth, the changes of 2 8*28 and 64*64 color images used for 3-layer CNN training are shown in Fig. 4 and 5, whiles the results are shown in Table 3.

Fig.4 shows the training and validation accuracy diagram of images of different sizes.

(a) Loss function for training and validation for 28*28 images (b) loss function for training and validation for 64*64 images.

Fig. 5 the diagram of loss functions for training and validation of images of different sizes

Fig.4 and 5, show the lost function diagram for training and validation of images of different sizes. The blue represents the

Fig.4. The diagram of training and validation accuracy of images of different sizes

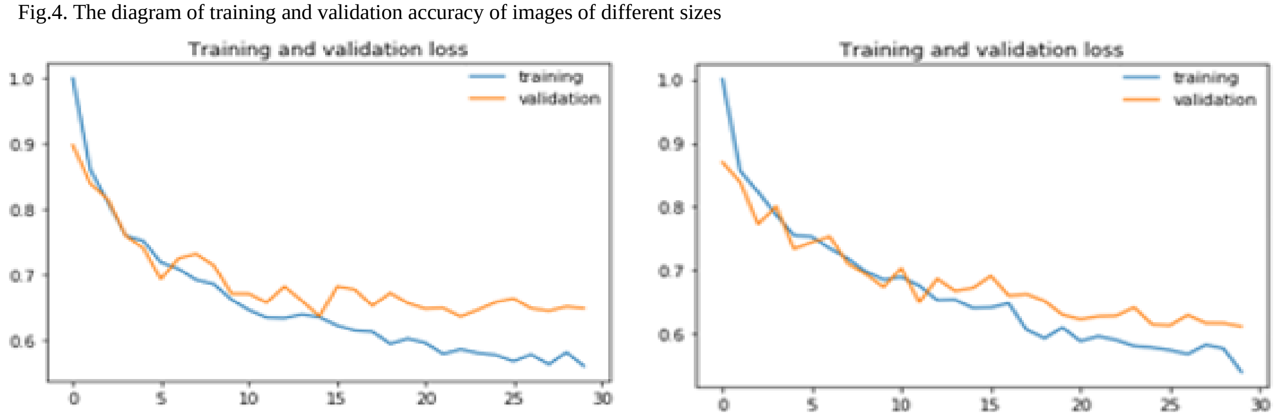

Fig.5. The diagram of loss functions for training and validation of images of different sizes.

training set's accuracy and loss function changes, and the yellow represents the training accuracy and loss on the validation set. As can be seen from the results in Table 3, using the classic CNN structure, the accuracy of training and validation is lower, but the change of training and validation accuracy of 64*64 images is relatively more balanced. From the change of loss function, the training and validation of 64*64 images are also gentler. The training accuracy and validation accuracy show a gradual upward trend with the change in the number of cycles, and the training accuracy reaches 0. 7901, while the validation accuracy reaches 0. 7781. The loss function also shows a gradually decreasing trend.

TABLE 3 COMPARISON OF CLASSIFICATION RESULTS OF THREE DEEP CONVOLUTION NEURAL NETWORKS

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

TABLE 4 COMPARISON OF CLASSIFICATION RESULTS OF DEEP CONVOLUTION NEURAL NETWORK WITH OTHER LITERATURE

	Network	Accuracy
27 references	VGGNet-19	81.93%
	Inception-V3	81.01%
	ResNet-50	83.26%
This text	InceptionV3	85.80%
	ResNet50	86.69%
	DenseNet201	86.91%

To sum up, the following conclusions c an be drawn:

As can be seen from Table 3, DenseNet201 has a higher accuracy as compared to Table 4, and the 27 references accuracy rate is low. In table 3, each network test based on transfer learning constructed is higher, due to preprocessing or better selection of some network ranges. Therefore, before carrying out images classification experiment there is a need for sample preprocessing for optimal accurate results.

V. CONCLUSION

In recent years, the incidence of skin diseases has become higher and higher, and the incidence and mortality of melanoma have seriously impacted people's health negatively. It is difficult for experts to diagnose melanoma at an early stage and treat it radically, and sometimes even in the face of the same dermoscopy images, different experts may also give different conclusions. Therefore, 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 from ISIC2017 to analyze the skin lesion image data, and it's summarized as:

In order to achieve an optimal classification accuracy of the skin disease images, digital image processing techniques such as image cropping, color space transformation, and hair removal are used. Since the image samples are not balanced, two techniques of undersampling and oversampling are used for processing. And the experimental results show the classification accuracy of the preprocessed images is higher.

Also, a transfer learning method is applied to fine-tune the parameters of the ImageSet-based Inception V3, ResNet50, Xception, and DenseNet network models to achieve 224*224 grayscale skin disease image data classification. The results on table 3 shows that Inception V3, ResNet50, and DenseNet201 all achieved more than 95% training accuracy. After preprocessing, 224*224 skin disease image data are classified, and it is found that the three improved models have achieved better accuracy with the highst accuracy of 86.91% for DesNet compared with other literature with the highst accuracy of 83.26% for ReseNet50.

VI. FUTURE WORK.

In future works, the researchers aim to achieve higher success by improving the model and enriching the dataset. There is also the need to reach generalizable results, hence model could be tested with more varying skin diseases to make the application usable in practice.

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