

Studies on Different CNN Algorithms for Face Skin Disease Classification Based on Clinical Image

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Abstract

Skin problems not only injure physical health but also induce psychological problems, especially for patients whose faces have been damaged or even disfigured. Using smart devices, most of the people are able to obtain convenient clinical images of their face skin condition. On the other hand, the convolutional neural networks (CNNs) have achieved near or even better performance than human beings in the imaging field. Therefore, this paper studied different CNN algorithms for face skin disease classification based on the clinical images. First, from Xiangya–Derm, which is, to the best of our knowledge, China’s largest clinical image dataset of skin diseases, we established a dataset that contains 2656 face images belonging to six common skin diseases [seborrheic keratosis (SK), actinic keratosis (AK), rosacea (ROS), lupus erythematosus (LE), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC)]. We performed studies using five mainstream network algorithms to classify these diseases in the dataset and compared the results. Then, we performed studies using an independent dataset of the same disease types, but from other body parts, to perform transfer learning on our models. Comparing the performances, the models that used transfer learning achieved a higher average precision and recall for almost all structures. In the test dataset, which included 388 facial images, the best model achieved 92.9%, 89.2%, and 84.3% recalls for the LE, BCC, and SK, respectively, and the mean recall and precision reached 77.0% and 70.8%

1. Introduction

Based on a survey in 2010, skin diseases had the fourth leading cause of nonfatal disease burden in the world, and three of the world’s most common diseases were skin diseases . Skin diseases have caused enormous economic burdens both in high-income and low-income countries. For each individual, skin problems can have adverse effects on all aspects of life, including interpersonal relationships, work, social functioning, physical activity and mental health.

Usually, skin diseases cause skin lesions, scales, plaques, pigmentation and other symptoms on the patient’s skin . These symptoms result in long-term pain and disfigurement.

Such damage not only injures physical health but also contribute to serious mental problems, especially when such damage occurs on face. Studies showed that patients with primary skin diseases (such as psoriasis, alopecia areata and vitiligo) have a higher potential for mental problems, such as anxiety and depression. In addition, some skin disease treatments also have the possibility of inducing mental illness (such as isotretinoin, an acne medication, may induce suicidal depression).

Facial skin is exposed to the air almost all the time, so it has a higher risk of being damaged than other areas. Moreover, facial skin is the most important part of the body for people's appearance, so people are more concerned about their facial skin health than skin health anywhere else. Along with the availability of massive amounts data brought by the Internet [9] and the improvement of computing power brought by advanced hardware, deep learning algorithms have achieved human-level performance in many fields. For example, convolutional neural networks (CNNs) have made many breakthroughs in the field of medical image processing, especially for pathological, CT and MRI images, which have rigid features and high resolution. However, research on clinical images is relatively insufficient. For these reasons, clinical images always contain a very complex context, and it is hard to control the conditions of acquiring the image. These circumstances make image processing tasks difficult.

Furthermore, datasets of a certain part of the body, especially the face, re relatively scarce. At present, most of the available datasets are not clearly labeled with information on the body parts; for some datasets that provide this information, the proportion of facial images is always small . All of these conditions make research difficult. Therefore, this paper first constructed a skin image dataset based on 6 common facial skin diseases (seborrheic keratosis (SK), actinic keratosis (AK), rosacea (ROS), lupus erythematosus (LE), basal cell carcinoma (BCC), and squamous cell carcinoma (SCC)). It includes 2,656 facial images for a total of 4,394 images. We focus on these diseases for the following reasons: 1) LE, ROS, BCC and SCC frequently occur on the face; 2) AK and SK usually transition from benign to malignant without timely treatment.

Based on the dataset, experiments were carried out on 5 different CNN structures to verify whether these methods can effectively diagnose facial skin diseases using clinical images. In the test set consisting entirely of facial images, the structure named Inception-ResNet-v2 achieved the highest average precision (77.0%)

2. Literature Review

Many studies have applied deep learning algorithms to skin diseases . For example, the performance in the task of classifying skin tumors using the Inception-v3 network has reached the level of professional dermatologists; for nine classes of tumors, a computer achieved an accuracy of 55.4%, and two dermatologists achieved accuracies of 53.3% and 55.0% . Using the same network structure, achieved an accuracy of $87.25 \pm 2.24\%$ on the dermoscopic images for four common skin diseases, including SK, BCC, psoriasis and melanocytic nevus. These studies show that current deep learning methods have the potential to be applied to dermatoses.

At the same time, the application of deep learning to facerelated diseases is also promising. Reference designed a deep learning algorithm called DeepGestalt and trained their model on more than 17,000 real facial images of genetic syndromes, and this model can identify more than 200 genetic syndromes using facial images with relatively high precision. Reference investigated using CNNs to classify acne into different severity grades ranging from clear to severe, and their results show that the accuracy of their method outperformed expert physicians. Initially, we investigated the proportion of facial images in the most commonly used public datasets for skin disease, which include AtlasDerm , DermIS , the ISIC Archive , Derm101 and Dermnet . Most of these datasets did not provide information about body parts. In [19], which does provide body parts information, there were only 195 facial images. It is difficult to perform further research on facial skin diseases using such limited data. As a result, building a specialized dataset for face images is extremely necessary for our research

An image is a two-dimensional picture, which has a similar appearance to some subject usually a physical object or a person. Image is a two-dimensional, such as a photograph, screen display, and as well as a three-dimensional, such as a statue. They may be captured by optical devices—such as cameras, mirrors, lenses, telescopes, microscopes, etc. and natural objects and phenomena, such as the human eye or water surfaces.

The word image is also used in the broader sense of any two-dimensional figure such as a map, a graph, a pie chart, or an abstract painting. In this wider sense, images can also be rendered manually, such as by drawing, painting, carving, rendered automatically by printing or computer graphics technology, or developed by a combination of methods, especially in a pseudo-photograph. An image is a rectangular grid of pixels. It has a definite height and a definite width counted in pixels. Each pixel is square and has a fixed size on a given display. However different computer monitors may use different sized pixels. The pixels that constitute an image are ordered as a grid (columns and rows); each pixel consists of numbers representing magnitudes of brightness and color

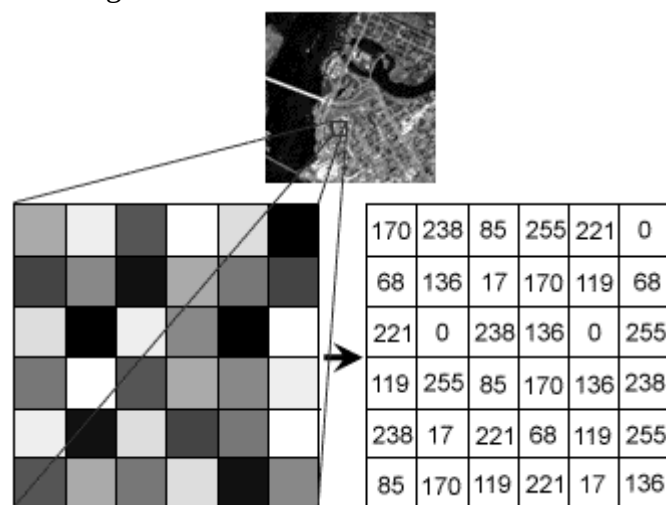


Fig 1: Image Pixel

Image compression uses algorithms to decrease the size of a file. High resolution cameras produce large image files, ranging from hundreds of kilobytes to megabytes, per the

camera's resolution and the image-storage format capacity. High resolution digital cameras record 12 megapixel (1MP = 1,000,000 pixels / 1 million) images, or more, in true color. For example, an image recorded by a 12 MP camera; since each pixel uses 3 bytes to record true color, the uncompressed image would occupy 36,000,000 bytes of memory, a great amount of digital storage for one image, given that cameras must record and store many images to be practical. Faced with large file sizes, both within the camera and a storage disc, image file formats were developed to store such large images

3. Proposed System

A neural network is a mathematical model inspired by the transfer process of biological neuron information, and its purpose is to learn a mapping from input to output. By using a loss function as a constraint and backpropagation to optimize the parameters, this method can automatically learn complex tasks for different fields. This method has reduced the need for human labor, such as manual feature extraction and data reconstruction for classification. A CNN is a type of neural network. It generally consists of an input layer, many hidden convolutional layers, and an output layer. Using this structure, the model can include a large number of parameters and obtain some usable properties, such as equivariance, for image-related tasks

we used five mainstream CNN algorithms that have been pretrained on ImageNet [9]. These five structures include ResNet-50, Inception-v3, DenseNet121, Xception and Inception-ResNet-v2. We used same pre-process for these images, including random reverse and crop. And to address the problem of data imbalance, we used different weights in the cost function for different diseases

ResNet adds connections between the shallow and deep layers of the network. Such connections directly transmit the information of the shallow layer to the deep layer. On the other hand, the propagation of the gradient to the shallow layer during backpropagation greatly increases the number of network layers .

The basic module of the Inception structure is the inception block. There are different kernels in a block, and each type of kernel has a different shape; the output of the block is combines the output from different kernels. This improves the diversity of the network in terms of width and the diversity of the scale of the receptive field. Therefore, the model improved its recognition performance for objects with different sizes.

DenseNet adds connections between each two layers; that is, the output feature maps of each layer will be used as the input for all subsequent layers. Using these dense connections, the network reuses features, thereby improving performance with fewer parameters, which makes the calculation more efficient .

Xception is an updated version of the Inception structure. Xception improves the Inception module with a depth wise separable convolution. This change decouples spatial correlations and cross-channel correlations. It can obtain a better performance than Inception-v3 with the same parameters . To some extent, Inception-ResNet is a combination of Inception and ResNet structures. By adding a residual connection to the Inception network, it can train deeper networks while maintaining the scale diversity of the network, thereby

enhancing the performance .

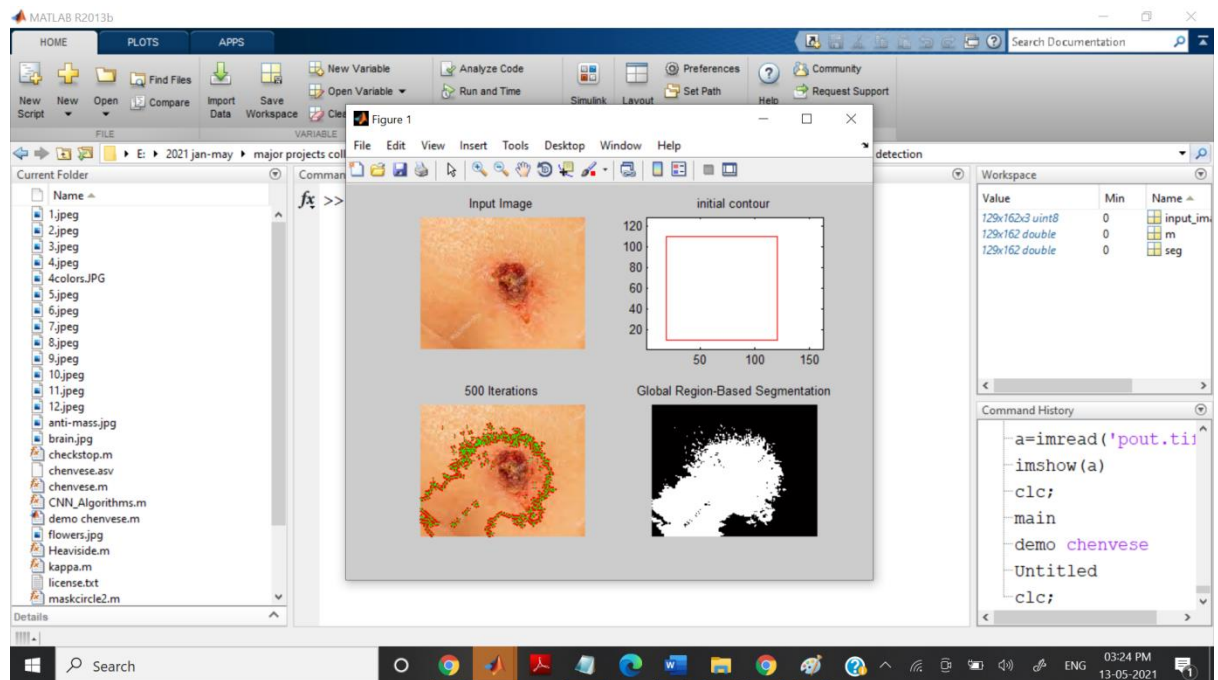


Fig 2: Proposed System output 1

we used the same 300*300 input images for each network and did not change the basic structure from that in their origin paper. We replaced the first fully connected layer behind the last convolutional layer with global average pooling and a 1*1 convolution to reduce the number of parameters and maintain spatial information. Finally, we used a 1024-d fully connected layer in each network and then used a soft max or logistic regression classifier to obtain 6 confidence outputs for six facial skin diseases. More details about the model structures are shown in Table 2, where inception block, dense block, transition layer, and inception resnet block are modules that are the same as those from the origin papers

MATLAB evaluates the list box's callback after the mouse button is released or a keypress event (including arrow keys) that changes the Value property (i.e., any time the user clicks on an item, but not when clicking on the list box scrollbar). This means the callback is executed after the first click of a double-click on a single item or when the user is making multiple selections. In these situations, you need to add another component, such as a Done button (push button) and program its callback routine to query the list box Value property (and possibly the figure SelectionType property) instead of creating a callback for the list box. If you are using the automatically generated application M-file option, you need to either:

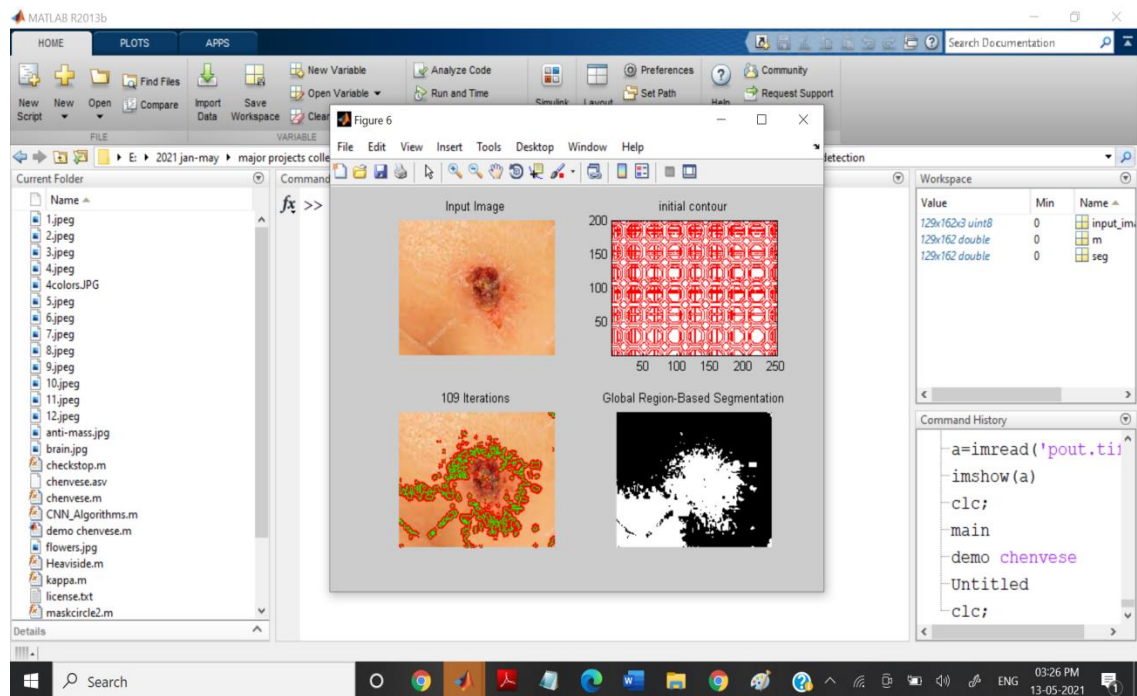


Fig 3: Output of the Proposed System 2

Set the list box Callback property to the empty string ("") and remove the callback subfunction from the application M-file. Leave the callback subfunction stub in the application M-file so that no code executes when users click on list box items.

The first choice is best if you are sure you will not use the list box callback and you want to minimize the size and efficiency of the application M-file. However, if you think you may want to define a callback for the list box at some time, it is simpler to leave the callback stub in the M-file.

4. Conclusion

This paper performed experiments using five mainstream CNN structures for the clinical image diagnosis of six common facial skin diseases and constructed a data set consisting mainly of facial skin disease images. The results demonstrate that CNNs have the ability to recognize facial skin diseases. Based on our experiments, we determined that different models to diagnose diseases on different body parts should be used. Furthermore, our experiments also showed that a more reasonable network structure could improve the performance of the model. The performance of the current network structure has been satisfactory in some diseases, but the overall performance has yet to be improved. As a result, if we want that people to actually use this technique to check their face skin health in their daily life, specialized improvements should be developed. In our opinion, the application of artificial intelligence techniques in the medical field is not sufficient, and the datasets from this field should be improved both in quantity and quality. With the increasing amount of facial image data of various skin diseases and the continuous improvement of the network structure, CNN-based facial skin disease diagnosis algorithms will continue to improve in

performance. We believe that, in the future, patients will use convenient CNN-based applications to keep their face skin healthy

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