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Skin cancer classifier based on convolution residual neural network

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ABSTRACT

Accurate automatic classification of skin lesion images is a great challenge as the image features are very close in these images. Convolution neural networks (CNN) promise to provide a potential classifier for skin lesions. This work will present dermatologist-level classification of skin cancer by using residual network (ResNet-50) as a deep learning convolutional neural network (DLCNN) that maps images to class labels. It presents a classifier with a single CNN to automatically recognize benign and malignant skin images. The network inputs are only disease labels and image pixels. About 320 clinical images of the different diseases have been used to train CNN. The model performance has been tested with untrained images from the two labels. This model identifies the most common skin cancers and can be updated with a new unlimited number of images. The DLCNN trained by the ResNet-50 model showed good classification of the benign and malignant skin categories. The ResNet-50 as a DLCNN has verified a significant recognition rate of more than 97% on the testing images, which proves that the benign and malignant lesion skin images are properly classified.

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1. INTRODUCTION

It is reported that there are 5.4 million new cases of skin cancer in the US alone and despite melanoma patients are less than 5%, it accounts for approximately 75% of all types of skin cancer in the US that related cause over 10,000 deaths per year [1], [2]. Melanoma is approximately 10 times more likely to spread and disseminate than all the other types of skin cancer, it is also very capricious and unpredictable most of the other types of skin cancers. It usually expects to see them in areas that are sun-exposed dominant or occupationally some exposed dominant melanoma on the other hand very unpredictable. It is seen around people's feet even in people's eyeballs are very unpredictable. The other problem with it is like an octopus it tends to borrow, and it has tentacles that tend to spread out quickly. Early detection of these cases is critical, where the 5-years survival rate drops from over 99% to 14% if detected in its latest stages [3]. According to [4]–[6], it is possible to classify human skin disease taxonomy, where red refers to malignant, orange denotes non-neoplastic, black for melanoma, and green refers to benign, as shown in Figure 1.

This classification figure has been prearranged visually and clinically with the help of medical specialists. Deep learning convolutional neural networks (DLCNN) skin image classifier enables to embed a dermatologist level classifier into our phone or personal computer (PC) by just snap a picture of user skin lesion and instantly getting such diagnosis [3]. A popular way of classifying images is that most images take

as input and by using a series of compositional filters and other miscellaneous things the deep learning communities come up with for better vision applications, and then match the images into class labels such as scattered off. The use of deep learning with an automated dermatology classifier will provide a new disease-partitioning algorithm for skin disease taxonomy that maps each disease according to training classes. The idea in this work is to detect skin cancer in clinical images by using a skin cancer classifier based on a convolution residual neural network. The considered data set in the paper consists of 320 clinical images including 160 benign and malignant classes. The skin lesion images have been resized to match the input of the DLCNN classification network. Residual network, which is called ResNet-50, as a DLCNN, is considered in this paper. ResNet-50 is a pre-trained architecture that is already trained on a database subset of the Image-Net for large-scale visual image recognition. A million images have been trained on ResNet-50, which has 177 layers corresponding to 50-layer residual networks. It can classify 1,000 images into object classes.

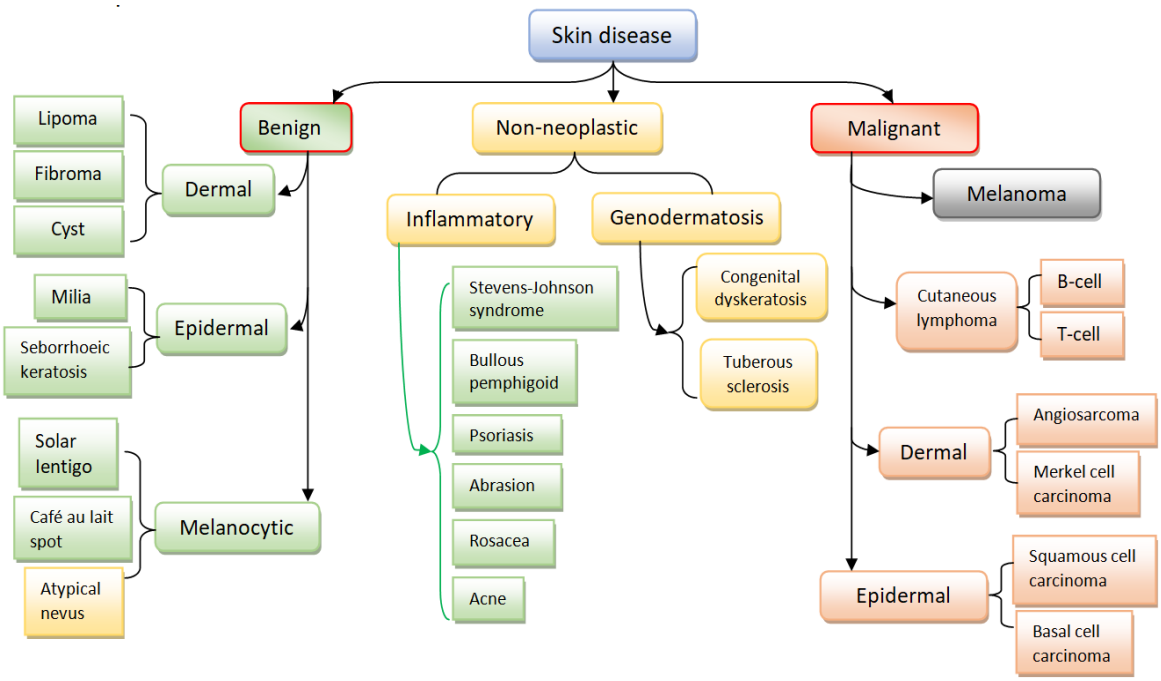

Figure 1. A diagram illustration of human skin disease taxonomy, where it is organized according to the clinical and visual similarity of the skin diseases [4]–[6]

Several deep learning techniques have been introduced to improve structure performance in solving different image processing and engineering problems. The learning techniques of DLCNN have undergone a large growth, which sharply improves its performance in various applications such as medical image classifiers [7], [8]. Several studies related to dermatological classifier [9]–[11] but they are have lacked to generalize the capability of disease-partitioning with unsatisfactory information and a spotlight on standard tasks like histological [12] and dermoscopy image classifier [13]. Histological images are obtained by invasive microscopy and biopsy, while dermoscopy images are obtained by a specific device, and both modalities create consistent images. Smartphone images as photographic images show inconsistency in features such as lighting, zoom, and angle, which makes a classifier significantly further challenging [14], [15]. Other previous related studies require extraction of visual features, lesion segmentation, and extensive processing, and pre-training before classification. In this work, a data-driven approach [16], [17] is considered to overcome these challenges. Hundreds of images with photographic variability are trained to ensure robust classification. In addition, no hand-crafted features are required in our system. The presented model trains the image raw pixels and labels by a single structure for dermoscopy and photographic images. This study presents a generalized classification approach with a flexible number of input clinical datasets that reach hundreds of thousands to generalize the application over extensive dermoscopy and photography images.

Advances in DLCNN with large-scale datasets [18] that recently create different visual tasks systems of human performances, for example; playing Atari game [19], [20], object recognition [21], [22],

and strategic games such as Go [23]. Hagerty *et al.* [24] used a utilized residual network algorithm called ResNet-50 as a DLCNN for image processing to fuse the features from individual methods by hypothesizing different error profiles and using three hand-crafted biological modules for predicting the probability of melanoma categorization. However, the adopted handcraft features-based method is not clear. In this work, an image-based classification using the CNN system is developed to match dermatologists satisfactory in some significant key diagnostic aspects such as melanoma/nonmelanoma classification by means of carcinoma and dermoscopy classifications. An open-source dataset have been pre-trained over approximately 1.3 million clinical images with large-scale object categories [25], and the dataset is trained using Renet50 learning architecture [26].

2. METHOD

2.1. Diagnosis

The convolutional neural networks (CNN) are trained with skin disease classes. Our dataset is organized with dermatologist-labeled clinical images that are coming from an online open-access clinical source. We divide the dataset into 70% for training images and validations, while 30% for testing images. An algorithm, that portioning skin diseases such as melanoma and non-melanoma, is developed as a fine training class. Initially, skin lesion images are separated from adjoining artifacts and normal skin tissue like hairs, air bubbles, and veils, with mean thresholding, color space transformation, and removal of the region of interest (ROI). Then, the region of interest image employing the binary mask image a set of features based on texture, shape, and color, is obtained. The features of deep learning neural network (DLNN) are acquired appropriate CNN structure that is trained in a MATLAB-function called ResNet-50 classification algorithm that includes CNN architecture to extract image features [27]. The obtained classification is trained on a dataset consisting of both benign and malignant skin-lesion images.

2.2. Resnet-50 architecture

The deep learning (DL) part of our approach depends on a transfer learning described in [27], and a deep residual network called (ResNet), which is a convolution-based architecture [28]. Its input matrix can accept 224×224 red-green-blue (RGB) images. DL ResNet architecture is effective in a large-scale image visual recognition to classify 1,000 objects [29]–[32]. ResNet can achieve a correct recognition error of 3.6%. ResNet is a convolution-based architecture. Bicubic interpolation is usually used to reduce the resolution. A sequential series of residual blocks as shown in Figure 2 is the main property of ResNet, which results in 2,048 feature vectors.

Since this work considers the residual network as a DLCNN to solve accurately the clinical skin lesion image recognition problem, the underlying architecture is illustrated layer by layer, starting from an RGB image to an output production, including convolutional layers, batch normalization layer, and max-pooling layers. There are too many convolution layers attached one by one, and there are many skip connections called residual neural networks. A main conceptual block diagram of the proposed approach is demonstrated in Figures 3, 4, and 5. To make the structure simpler to understand, the complete architecture is broken down into 19 small blocks. The first block is shown in Figures 3(a) to 3(c).

It is known that transfer learned models have a predefined shape, which is in the start described by 1×3×224×224. The first one shows the batch size, then the number of RGB channels, then 224×224 are width and height of an input image. ResNet-50 is applying 64 convolutions of 7×7 kernel size and a padding of 3 and strides of 2 that represent the tensor operation. The size of the image after padding is the same as width but when applying the kernel impact the size will be reduced to 230 after padding. The output from this first convolutional layer is 64 and the output size will be 1×112×112×64. The batch normalization applies to a simple layer and there are 64 mean variance beta and lambda which is the scaling factor that does not make any changes with the tensor other than normalizing. In the second block, the max-pooling is applied, which has strides 2, padding 1, and the kernel size 3×3. This is shown in Figure 4.

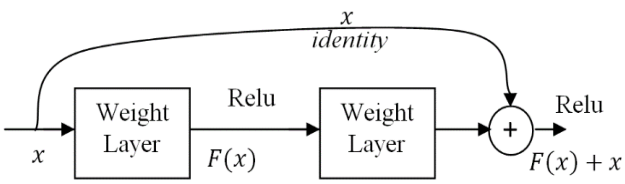

Figure 2. Residual block of ResNet-50 [28]

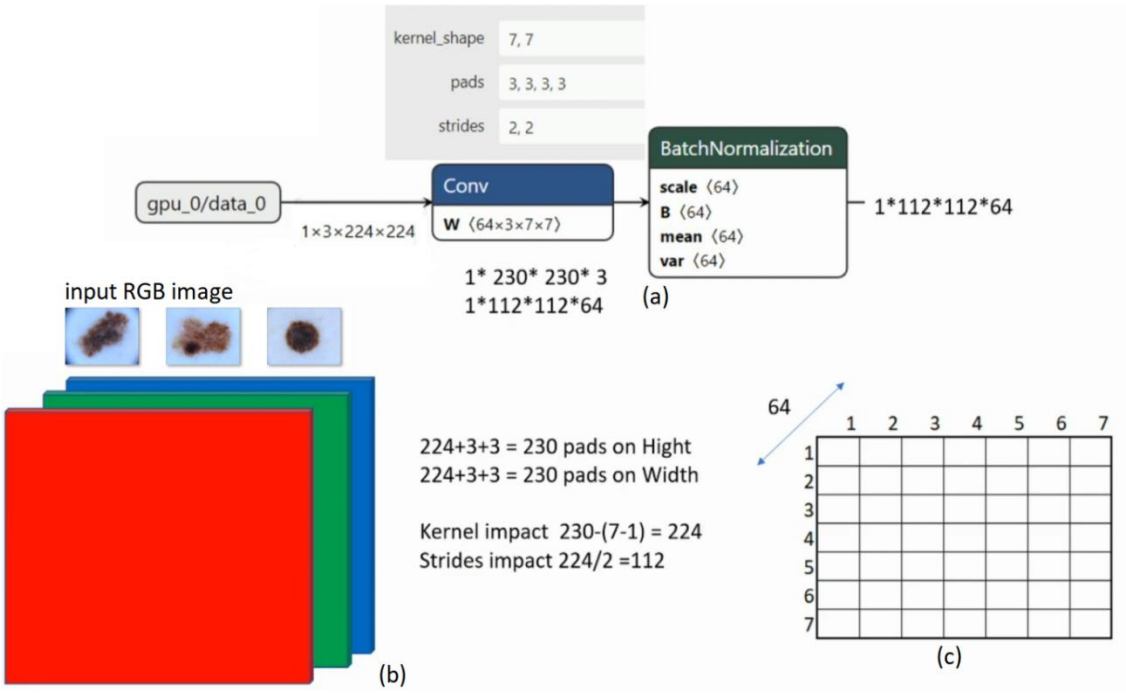

Figure 3. Block 1 of 19 ResNet-50 architecture, where (a) represents the 1st convolution operation, (b) the RGB input image, and (c) 7×7 kernel shape

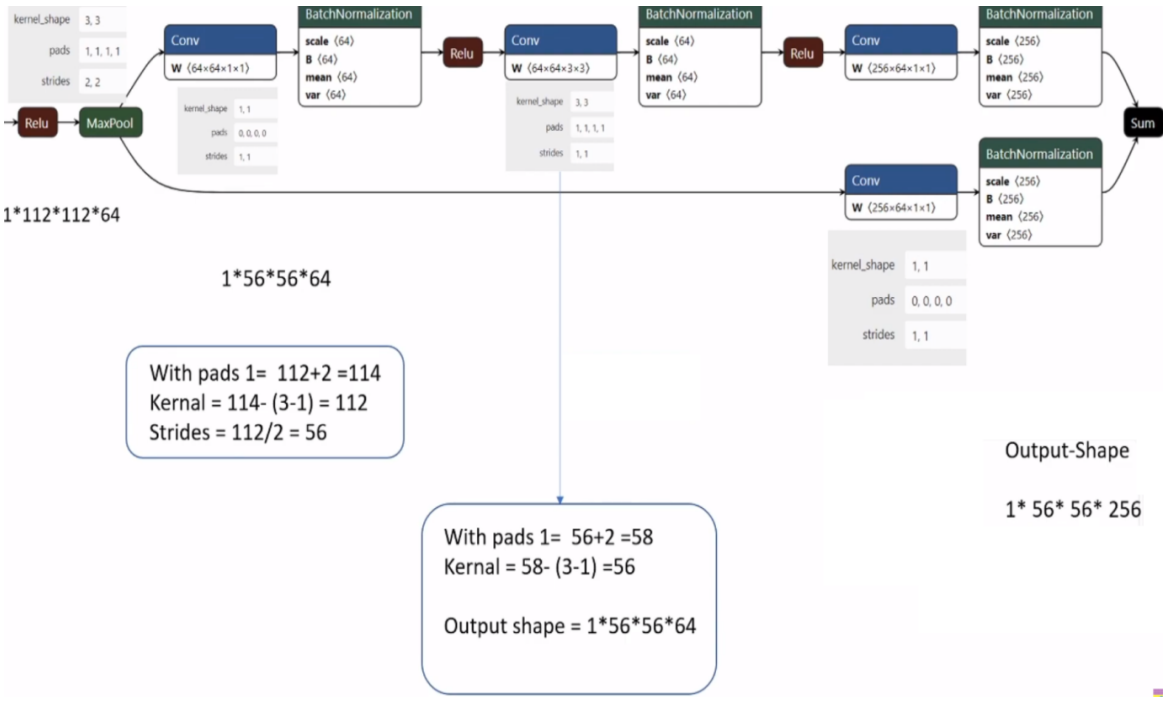

Figure 4. Block 2 of 19 of the ResNet-50 architecture

Therefore, the size is reduced and the complete shape is divided by 2 and the output shape will be 1×56×56×64. In this block, we have multiple convolutions on one side, then pass normalization, and the input dimension will remain the same. Another one convolution, which has the same kernel 1×1 padding, and strides are also 1×1 that makes no changes with the shape. There is a parallel connection with the simple shape of 256×64×1×1 that provides output 1×56×56×256. Therefore, only 64 got converted to 256.

Going forward in the CNN, these blocks are similar in nature actually, they are just tacked up one by one. The last end of this chain is having 256 filters in one convolution. So, it will again change the shape to 256 and this skip connection, which has been taken from this value (denoted by Relu), which is directly connecting to the sum. Getting understood of block 2 and block 3 all rest of the blocks are similar in nature. The last block of the ResNet-50 architecture is shown in Figure 5.

The last layer or block 19 includes applying an average pooling of 7×7. The average pooling is a little bit different though converting the 7×7 to 1×1 within one channel of 7×7. The output will be 1×2,048. Then a general matrix multiplication that is inclusive of softmax here. The output of the softmax is 1,000 classes and the input to the softmax is 2,048. Therefore, using this complete ResNet-50 CNN, this last softmax layer can be replaced by a defined number of classes and keeping all previous layers not trainable.

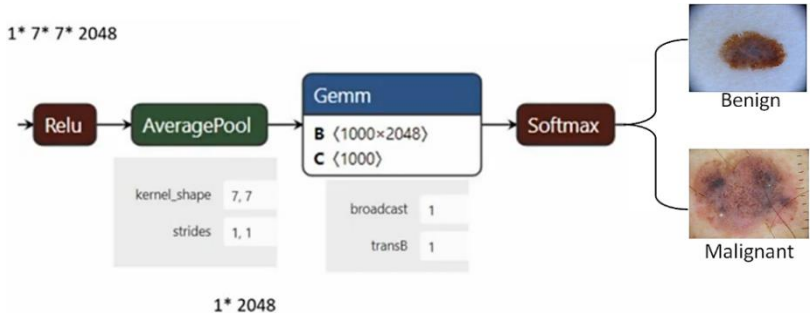

Figure 5. The 19th (final block) of 19 of the ResNet-50 architecture

3. RESULTS

The feasibility of the developed DLCNN to categorize the skin lesion images is verified by training 70% of the dataset and testing the remaining images that are not identified by the network. All patches of the residual CNN (ResNet-50) were (n=1,687), trained, and augmented in the training cohort in ResNet-50 to enlarge the robustness of the architecture. The upper graph of Figure 6 demonstrates the accuracy during the learning, which was found to be 0.9779, while the cross-entropy loss was close to 0.132 after 8th epochs training (248 iterations), which can be seen at the bottom of the figure. The elapsed time here was 1 min 0 seconds as the hardware resource is a single central processing unit (CPU) and not graphics processing unit (GPU). The details are also shown in Figure 6.

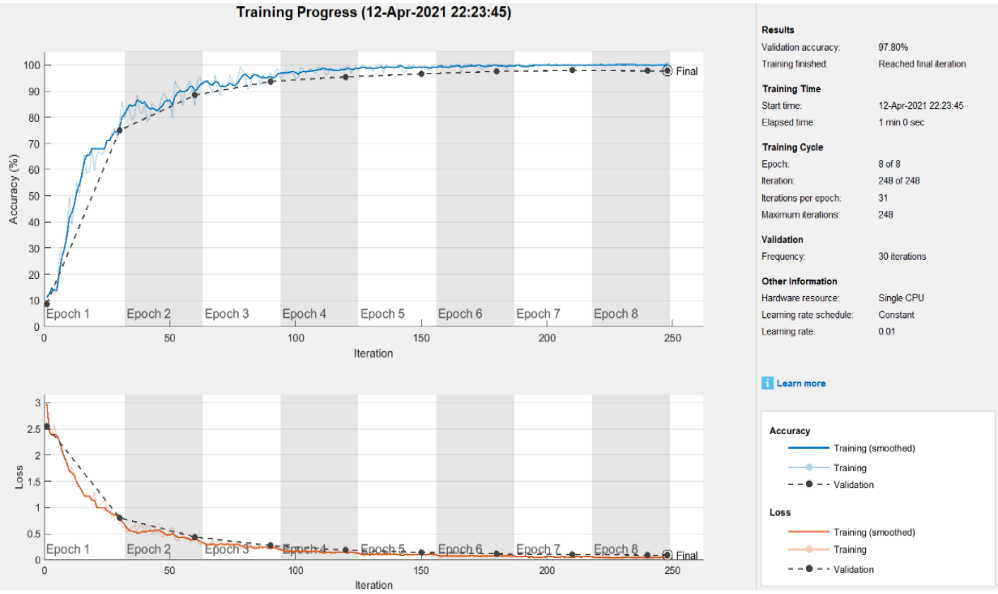

Figure 6. The process of training and validation of the DLCNN using ResNet-50 model when training skin lesion images

The accuracy is in the upper while the cross-entropy loss is in the bottom. Two categories have been classified over 248 maximum iterations. The input image is responded to or activated by each layer of the DLCNN. Some of these layers are performing the extraction of image features. The basic image features such as edges and blobs are captured by DLCNN at the beginning layers of the network. To take visual insight for the network filter weights, Figure 7 shows weights samples at the 1st convolution layer.

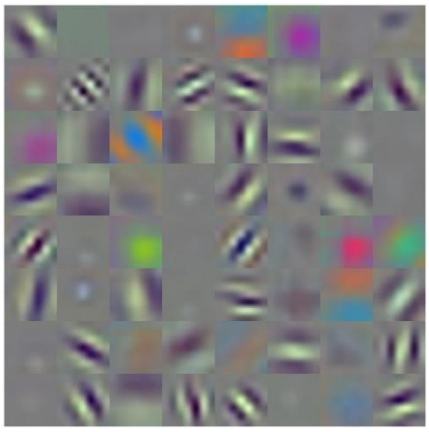

Figure 7. First convolutional layer weights

The DLCNN trained by the ResNet-50 model showed good classification of the benign and malignant skin categories. The ResNet-50 in DLCNN verified a significant recognition rate of more than 97% on the testing images, which proves that the benign and malignant lesion skin images are properly classified. Now, the predictive accuracy of DLCNN architecture can be obtained in each patch by a confusion matrix, which is displayed in Figure 8.

This study can be extended for future work by suggesting other models of deep learning or other diseases [33]–[40]. In addition, one can enhance the present research by designing embedded systems based on field-programmable gate array (FPGA) to implement the classifier within real-time environment [41]–[52].

Benign	47	1	
Malignant	4	44	
	Benign	Malignant	97.80%

Figure 8. Confusion matrix

4. CONCLUSION

This paper presents a developed residual network as a deep learning CNN for image recognition purposes to classify the lesion skin images into benign and malignant images. About 320 clinical images of the different diseases have been used to train CNN. Deep ResNet-50 network with skip connections was employed as an approach to perform the partitioning images task, which results in higher classification performance. The results of training and the verification by the testing images show that ResNet-50 DLCNN is efficiently able to accurately generalize the grade of benign and malignant images with a very small margin of error. The significance and robustness of this model in grading skin lesion images are because of its control of learning high and low levels to extract image features utilizing its deep residual networks, pooling layers, skip connections, layer depth, and convolutions. These features help to extract unimaginable features that contribute to reaching high recognition rates throughout the training of the network. Such

recognition architecture must be assigned as the mainly efficient, accurate, errorless, reliable, and flexible models for image partitioning to classify clinical lesion skin image applications.

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