Convolutional Neural Network Algorithm with Parameterized Activation Function for Melanoma Classification

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***Abstract* — Melanoma is the deadliest form of skin cancer, which is considered one of the most common human malignancies in the world. Early detection of this disease can affect the result of the illness and improve the chance of surviving. The tremendous improvement of deep learning algorithms in image recognition tasks promises a great success for medical image analysis, in particular, melanoma classification for skin cancer diagnosis. Activation functions play an important role in the performance of deep neural networks for image recognition problems as well as medical image classification. In this paper, we show that a deep neural network model with adaptive piecewise linear units can achieve excellent results in melanoma recognition. Experimental results show that a convolutional neural network model with parameterized adaptive piecewise linear units outperforms the same network with different activation functions in the melanoma classification task. All experiments are performed using the data provided in International Skin Imaging Collaboration (ISIC) 2018 Skin Lesion Analysis towards Melanoma Detection.**

Keywords—Melanoma, Skin Cancer, Deep learning, Convolutional Neural Networks

I. INTRODUCTION

Deep learning algorithms, especially Convolutional Neural Networks (CNNs) have been used for computer vision tasks for decades. Recently, the availability of large-scale datasets and the development of very powerful GPUs have allowed researchers to make CNNs very deep. For instance, a deep CNN network called AlexNet, proposed by Krizhevsky et al. [1], achieved excellent performance (top-1 and top-5 error rates of 37.7% and 17.0%) in the 2012 ImageNet Large Scale Visual Recognition Challenge. There was no clear understanding of why deep CNNs show very good classification performance until the visualization technique proposed by Zeiler et al. [2] provided an intuitive understanding of the functions of intermediate feature layers. Additionally, some other algorithms based on deep CNNs have also demonstrated very good performance in image classification, such as [3-4].

Skin cancer is one of the most common types of cancer around the world and statistically, it represents more than half of cancer diagnoses. There are two basic types of skin cancer named non-melanoma and melanoma, much rarer, however a much more serious disease. Its incidence and overall mortality rates have been rising in recent decades [5], therefore represents a substantial public health problem. Up to one-fifth of the patients develop metastatic disease, which even may lead to death. However, a patient's prognosis can be considered good when the melanoma is detected in the early stages. Early detection and appropriate excision lead to a cure rate of over 90% in low-risk melanoma patients. Innovative early detection programs, in combination with improved diagnostic tools and new immunologic and molecular target treatments for advanced stages of the disease, may influence the outcome of the disease in the future [6].

In this work, we discover the role of activation functions in the hidden layers of deep neural networks for medical image classification. And we propose a deep CNN algorithm for classification of possible melanoma diagnosis using skin lesion images. We use image data that is extracted from ISIC 2018: Skin Lesion Analysis Towards Melanoma Detection" grand challenge datasets [7-8].

The rest of the paper is organized as follows. Section II gives a brief review of deep learning algorithms for medical image analysis. The architecture of our CNN network for melanoma classification is illustrated in Section III. Experimental results are demonstrated in Section IV. Section V concludes the paper.

II. RELATED WORK

This section provides a review of previous research on deep CNN for pattern recognition, in particular, medical image analysis.

Despite the fact that real power of CNNs have been discovered recently, applications of CNNs in medical image analysis can be traced to the 1990s, when they were used for computer-aided detection of microcalcifications in digital mammography [9], and computer-aided detection of lung nodules in CT datasets [10]. With revival of CNNs owing to the development of powerful GPU computing, the medical imaging literature has witnessed a new generation of computer-aided detection systems that show superior performance in many tasks including computer-aided detection of lymph nodes in CT images [11], computer-aided detection of pulmonary embolism (PE) in CT datasets [12], automatic polyp detection in colonoscopy videos [13-14]. Researches and developments of CNNs in medical image analysis are not limited to only disease detection systems, however CNNs have recently been used for skins lesion classification problems [6], pancreas segmentation in CT images [15], carotid intima-media thickness measurement in ultrasound images [16-17], multimodality isointense infant brain image segmentation [18], and neuronal membrane segmentation in electron microscopy images [19].

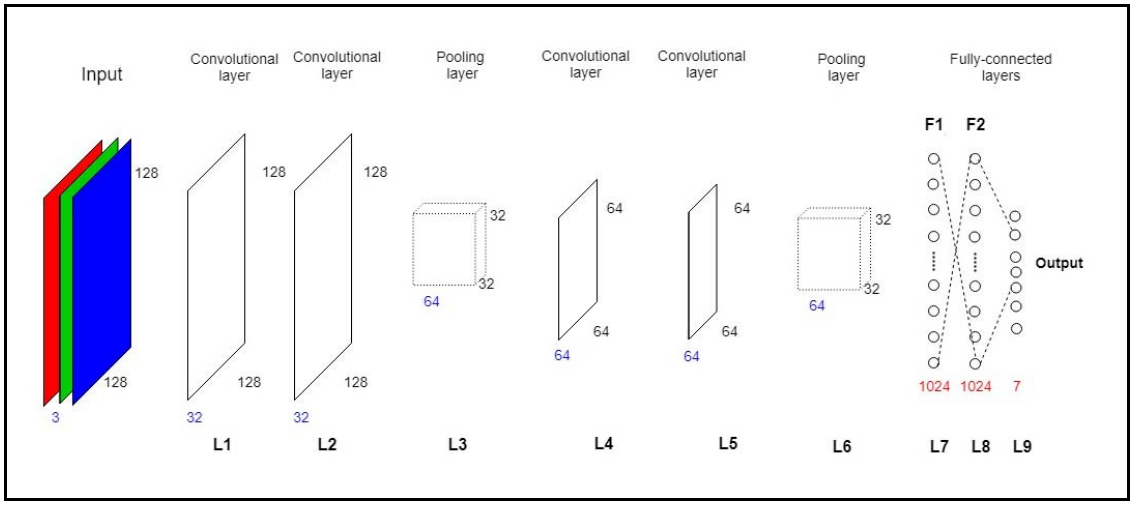

Fig. 1. The architecture of the deep CNN for skin lesion disease classification. The network consists of nine layers: four convolutional layers (parallelograms with solid lines), two max-pooling layers (parallelograms with dotted lines) and three fully connected layers at the end. Blue numbers under parallelograms denote the number of filters, black numbers denote the widths and heights of the feature maps and red numbers denote the number of neurons in the fully-connected layers

III. Proposed Approach

A. Image Data

The training data for lesion diagnosis which consists of 10015 images are downloaded from ISIC 2018: Skin Lesion Analysis towards Melanoma Detection" grand challenge datasets [7-8]. There are seven possible disease categories: Melanoma, Melanocytic Nevus, Basal Cell Carcinoma, Actinic Keratosis, Benign Keratosis Dermatofibroma and Vascular Lesion as illustrated in Figure 2.

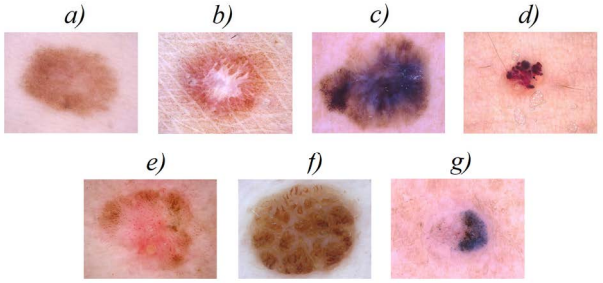

Fig. 2. Example images from Skin Lesion Image dataset for following disease diagnostics: a) nevus; b) dermatofiboma; c) melanoma; d) vascular; e) pigmented Bowen's; f) pigmented benign keratoses; g) basal cell carcinoma

B. Proposed CNN Network

We have created a simple CNN for melanoma classification using some of the ideas fundamental to LeNet [20], which was applied to recognize hand-written characters. Considering the fact that we need a deeper network for this task we add more layers and the final version of our network consists of 9 layers, as shown in Figure 1. The network has four convolutional and two pooling layers for feature extraction, and three fully-connected layers, in the end, for classification.

The main modification we make to the LeNet approach in our CNN model is using the adaptive piecewise linear activation (APL) function [21], instead of using traditional activation functions in convolutional layers. This contribution improves the performance of the network, despite having some additional features which increase the training time (the detailed experimental results are shown in Section IV).

IV. Experiments and Results

All experiments are performed using the Keras [22] software package on the Ubuntu 16.04 operating system, running on a PC with Intel(R) Core(TM) i7-7700HQ CPU 2.80 GHz with a Nvidia GTX 1050 Ti GPU.

A. Experiments with Different Activation Functions

To demonstrate the advantages of using APL units over traditional ReLUs and tangent functions, we compare the results of our deep CNN network model with APL units in hidden layers versus ReLU functions and tangent functions. We only change the activation functions of our model to ReLU and tangent functions; other hyperparameters remain unchanged. We train all networks using the training dataset which consists of 10015 skin images and evaluate using a test set which has 1500 images. Evaluation results, listed in Table 2, show that our network performs better with APL units in hidden layers than with ReLUs and tangent functions.

TABLE I. Evaluation of performance of our deep CNN with different activation functions.

Activation functions	Test accuracy	
	With data augmentation	***Without data Augmentation***
ReLU	93.25%	92.36%
Tangent	91.76%	91.15
APL units	**95.86%**	**93.42%**

Moreover, our network with APL units reaches the highest training accuracy around 98 % after about 65 epochs, and then it remains stable. The training accuracy of the same network with ReLUs and tangent functions is not higher than 96 %, and they become stable after about 150 and 200 epochs respectively. This means that our network consumes

fewer computing resources and works faster to learn features of fire and smoke when it has APL units in hidden layers than when it has ReLUs and tangent functions. The detailed training process of our network with different activation functions is illustrated in Figure 3.

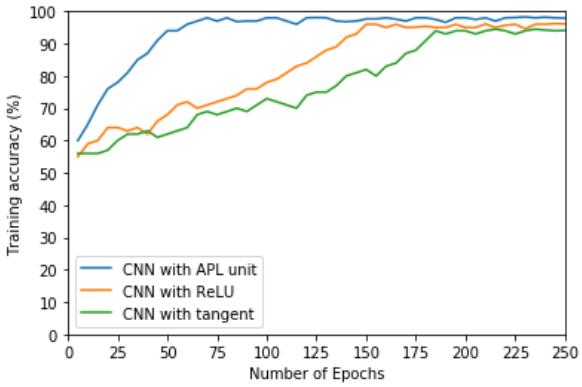

Fig. 3. The training curves of the deep CNN with different activation functions.

V. Conclusion

In this paper, we showed that with the help of deep learning method high-quality diagnosis can be predicted for skin lesion diseases. We created a deep CNN for skin lesion classification by adding the adaptive piecewise linear function, which facilitates notable performance improvements in our model, without significantly increasing the number of learnable parameters.

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