AUTOMATIC DIAGNOSIS OF SKIN CANCER USING DERMOSCOPIC IMAGES BY DEEP LEARNING

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ABSTRACT

In computer-based skin cancer detection, segmentation is the first and most crucial activity because other activities rely on correctly segmented lesions. Deep learning, a popular machine learning technique, has recently produced encouraging results for semantic image segmentation. The two main segmentation problems in melanoma diagnosis that deep convolutional networks address are lesion segmentation and lesion dermoscopic feature segmentation. The suggested model includes two standard feature extraction modules for a feature discrimination network and a lesion classification network. Our study introduces a novel approach for lesion recognition that combines a lightweight CNN for initial feature extraction with dual classification and feature discrimination networks for enhanced learning. By integrating a model fusion technique, we significantly refine the system's accuracy with a leaner model structure. We propose a streamlined semantic segmentation model for dermoscopy images' lesion areas, leveraging the U-Net architecture and a transfer learning strategy to bypass complex preprocessing, achieving high-precision segmentation. Our comprehensive evaluation demonstrates superior performance over existing deep learning solutions, showcasing the effectiveness of our methodology.

Keywords: Skin cancer detection, Dermoscopy Images, Lightweight deep learning network, Fine-grained features, and Semantic Segmentation.

I. Introduction

Cancer research organizations from all around the world continue to focus on the fatal form of skin cancer known as melanoma. Even while new cases arise often, if caught early enough to cause harm to other bodily parts, it is most likely to be treated. Thus, it has been recognized as a challenging task that not only calls for expert dermatologists and specialized technology but also requires the accurate early detection of melanoma. However, early detection might be achievable using computer-based diagnostic tools that use machine learning and image processing methods.

The initial step in diagnosing melanoma is lesion segmentation; feature extraction and categorization follow. Many picture segmentation methods have been developed for this problem, such as fuzzy c-means, a clustering-based method—region expanding, and type-2 fuzzy logic-based picture thresholding. Active contours based on regions and edges have also been linked to lesion segmentation tasks. Another effective technique uses a Gaussian low-pass filter followed by global thresholding calculated using Otsu's method. Hybrid segmentation techniques have proven effective in several medical segmentation studies. To extract information from segmented images for pattern analysis, which can help identify melanocytic lesions, image processing methods have been created. The ABCD factors—asymmetry (A), border (B), color (C), and dermoscopic structure (D)—are distinct markers of skin cancer that can be evaluated using a variety of methods.

This has been accomplished by applying feature extraction techniques based on wavelet and Fourier transformations. Apart from textural features obtained through wavelet decomposition, boundary-series analysis, and geometric measurements have been applied in both the spatial and frequency domains. Discrete cosine transform and fast Fourier transform were employed in the suggested automated analysis of skin lesions. This strategy was used for the colour feature set and the pigment network feature. Computer-assisted skin cancer diagnosis systems utilizing recognition and detection techniques have also extensively used artificial neural networks. In various applications, artificial neural network-based predictive approaches have demonstrated a surprising capacity to tackle non-linear modeling problems; nevertheless, most of these methods use shallow architectures because deep network training is difficult. Recent advances in fast learning algorithms and the superior performance of deep artificial neural networks over more traditional approaches in several pattern recognition

and machine learning applications have drawn much attention to deep designs.

Convolutional neural networks have been introduced as a deep neural network design comprising numerous layers, in contrast to traditional artificial neural networks that use shallow nets. The main advantage of using a deep network design is that it makes it possible to automatically and passively get more complicated features from a larger range of layers. Convolutional neural networks have been applied in recent medical research, especially in identifying melanoma. While there have been few segmentation experiments, the categorization problem has attracted greater research interest.

A newly constructed hybrid architecture that incorporates hand-coded feature extractors, sparse-coding techniques, and a fully convolutional U-Net architecture was developed to examine the problem of melanoma recognition and segmentation in dermoscopic images. Nevertheless, dermoscopic feature segmentation is separate from the tasks in their study, which also involves classification and lesion segmentation. Usually, doctors can differentiate between benign skin lesions and melanoma (cancer) using the dermoscopic features.

Therefore, it needs to be looked into. To accomplish this, this paper examined the localization of two characteristics (streaks and globules) in addition to lesion segmentation. As a result, a deep network-based feature learning method specifically designed for lesion segmentation has been developed. For this experiment, a photo dataset from the 2016 ISBI (IEEE International Symposium on Biomedical Imaging) competition was made accessible to us.

The fully convolutional neural networks form the foundation of this study's deep architecture [22]. We chose a pre-trained model instead of creating the network from scratch because of the small dataset and the requirement to save training time. The two tasks are (i) segmenting the lesion at first and (ii) segmenting its dermoscopic features afterward. These were part of the ISBI challenge for skin lesion analysis towards melanoma diagnosis and are the subject of this study. Pre-trained models on medical images are rather rare, while semantic image training has been used in most convolutional neural network studies.

Although the model built in the first stage was employed, a pre-trained model trained on real photos was used for the second assignment of the study's first task. In addition to dropout layers, we employed data augmentation methods, including

image flipping and cropping, to prevent overfitting. The remaining sections of the essay are arranged as follows: Lesion segmentation and segmentation of lesion dermoscopic characteristics are the two topics covered in Section II. Section III presents the analysis's findings. The next sentence is "Conclusion of Section IV."

II. Objective of The Study

- To create a DCNN-based model that can accurately and automatically categorize different forms of skin cancer into melanoma and non-melanoma categories.
- Using several DCNN architectures, a systematic approach was examined to categorize skin cancer as melanoma and non-melanoma.
- The concerns with a class imbalance in the dataset and various image resolutions related to skin classification were addressed.

III. Methodology

Finding a dataset big enough to train a full convolutional network from scratch with random initialization is uncommon. We have, therefore, looked at data augmentation. According to this method, two models developed using semantic rather than medical pictures were used to fine-tune the deep network for lesion segmentation. The work of segmenting lesion dermoscopic features is also part of the methodology's last step.

A. Data Augmentation

The information used in this study is derived from the ISBI 2016 challenge "Skin Lesion Analysis Towards Melanoma Detection," This utilizes an ISIC Archive dataset of photographs with skin lesions labeled [21]. The dataset's sample mix of photos represents both benign and malignant skin lesions. The dataset was randomly divided into training and test sets, with the training set including 900 colored JPEG images and the test set including 379 images. The train and test images have pixel sizes ranging from 722542 to 42882848. Because these photographs are too huge to fit entirely in memory, they have been cropped and reduced to 500500. The dataset's size has also been increased through flipping. Seven thousand two hundred colored images were increased in the number of photos for training by cropping them in half and flipping them in all directions (vertically, horizontally, and both).

Lesion Segmentation

The original image and a deft manual tracing of the lesion boundaries as a binary mask are included in this work's image data set from the ISBI 2016 challenge.

Dermoscopic images are used as test data to predict lesion segmentation

borders. The topic of data augmentation was covered in the previous section. Another method for instructing a network using limited datasets is to apply the pre-trained network's weights and additional back-propagation-based training to fine-tune.

It is possible to carry on improving only the upper tiers of the network if there is a problem with over-fitting or if all network layers have been updated. The shallow model, VOC-FCN8s, which has 15 convolutional layers, and the deeper model, FCN-Alex Net, which has seven convolutional layers each, were adjusted for this work [22].

The GeForce GTX TITANX GPU was used to construct the deep network. The caffeine deep learning framework was created by the Berkeley Vision and Learning Center (BVLC) and community contributors; it was released under the terms of the BSD 2- Clause license [23]. The deconvolutional layers of the deep network follow the convolution and pooling layers. Pooling layers follow normalization layers.

Skip connections are a concept that has also been used in deeper architecture [22]. We looked into what would happen if the filter size or pooling layer stride were reduced to increase accuracy. Convolutional and pooling layers alone made up the whole network design offered by All Convolutional Net [24]. To reduce the size of the representation, they suggested using convolutional layers with larger strides. Here, we reduced the stride of the final pooling layer to provide higher-quality inputs for the up-sampling levels. This increased the computing load but needed improvement in accuracy. A generalized illustration of the recommended network design is shown in Fig. 1.

B. Lesion Dermoscopic Feature Segmentation

The second challenge has been figuring out patterns in the dermoscopic lesions. Clinicians can distinguish between benign skin wounds and melanoma using dermoscopic characteristics like globules and streaks. The objective is to automatically create these masks for the test data to indicate where features are present in lesions using the binary masks provided as training data. Figure 1 displays an example of how the database is represented. The database contains 807 jpeg images, 1614 png binary mask images (different masks for the dermoscopic properties of "globules" and "streaks"), and 335 test images. Photos have been trimmed using a

bounding box around the lesion area with training ground truth photos from a previous challenge. We used a factor of 1.1 to crop the images since streak features could be ejected from the lesion's edge. In the testing phase, test images have been cropped before entering the network using masks produced by our lesion segmentation. To aid in the network's speedy convergence, we included equivalent convolutional layers in this phase and initialized them using a pre-trained model from the preceding section. This design is then split into two portions, each having two convolutional layers and four deconvolutional layers, to predict masks for both streaks' and globules' features. We used crop, convolutional, and fusion layers to blend older, shallower pooling layers with up-sampling layers. To achieve this, we used the same concept to mix high-layer and low-layer data.

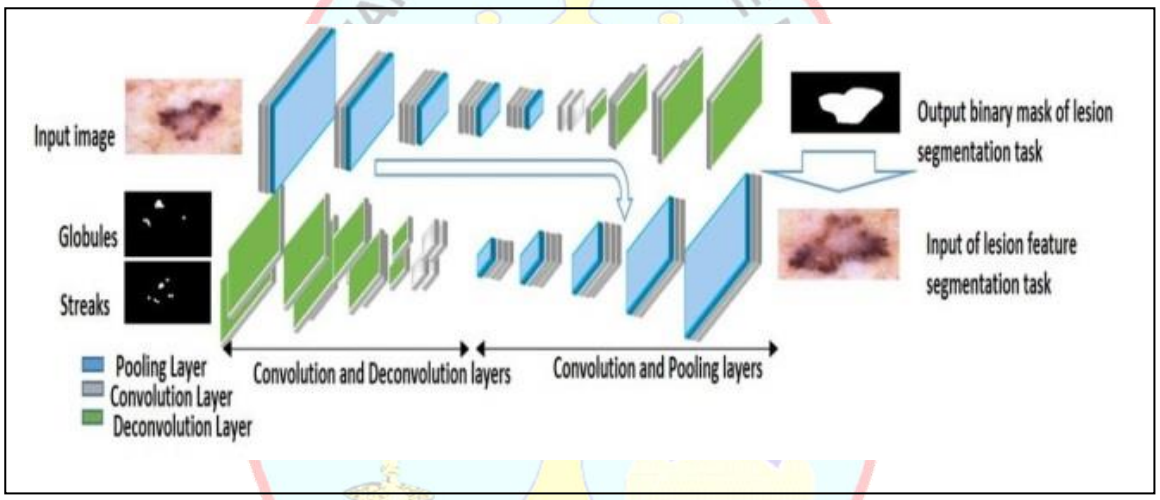

Figure 1 shows the deep network architecture overview for segmenting dermoscopic features and lesions tasks.

IV. Results

The deep learning-based approach for melanoma diagnosis was developed using two different deep learning-based networks. Convolutional networks are utilized to segment lesions and dermoscopic features, respectively. Using the stochastic gradient descent (SGD) method, both networks were trained with weight decay and momentum set to 0.0005 and 0.9, respectively. Over time, the learning rate was manually decreased during the training phase from 0.0001 to 0.001. The kernel sizes were set at 33 for the convolutional layer and 22 for the pooling layer. Figure 2 demonstrates how flipping, cropping, and applying a deeper network to the database can have an impact. Deep network-generated output mask shows a substantial improvement. Every one of the output

metrics has been improved by employing cropped photos and a more in-depth pre-trained model.

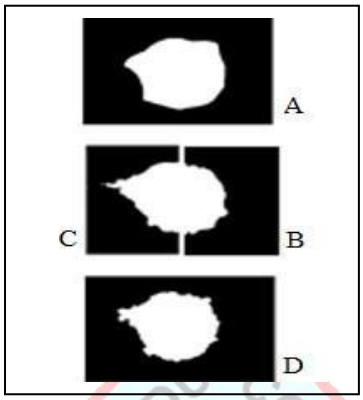

Figure 2. (A) image divided by the model learned on Alexanet; a simple flip expands the set of data, (B), (C) Cropping and flipping were used to improve the data set, and a deeper network (16 convolutional layers) with the pre-trained model VOC-FCN8s produced two cropped segmented images. (D) Illustration of a ground truth test.

METRIC / METHOD	SE	SP	AC	JA	DI
Best Outcome of the Challenge	0.91	0.96	0.95	0.84	0.91
(7200 training photos) Deeper model with 16 convolutional layers enhanced by flipping & cropping	0.91	0.95	0.94	0.83	0.89
Flipping is added to a model with seven convolutional layers (3600 pictures).	0.82	0.93	0.91	0.67	0.79
Without augmentation, a model with seven convolutional layers (900 pictures)	0.75	0.91	0.89	0.61	0.74

TABLE I. LESION SEGMENTATION EVALUATION RESULTS VS. BEST CHALLENGE RESULT

There was a 10% improvement in accuracy and a 3% increase in the Jaccard index. Using the original images as training data, the FCN-AlexNet model created Fig. 2. A, whereas the deeper model produced Figs. 2. B and 2. C using the supplemented training dataset gained by the cropped photos.

Thus, the segmented output shown in Fig. 2 can be generated by combining images B and C. Using five different measurements, all computed at the single-pixel level, the

approach is contrasted with the ISBI Challenge 2016 competition results. Those are the percentage of successfully detected positives measured by sensitivity (SE).

$$SE=TP/(TP+FN) \quad (1)$$

What makes an accuracy accurate is:

$$AC=(TP+TN)/(TP+FP+TN+FN) \quad (2)$$

The percentage of accurately detected negatives is measured by Specificity (SP).

$$SP=TN/(TN+FP) \quad (3)$$

The dice coefficient (DI), a statistic, determines how similar the two samples are. It is explained in the following way:

$$DI=2\times TP/(2\times TP+FN+FP) \quad (4)$$

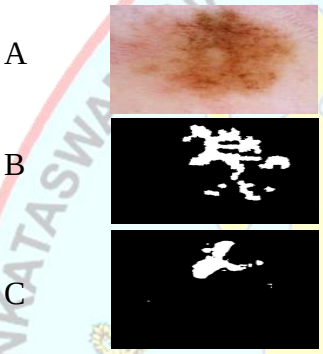

Figure 3. picture (A) from the dataset under test. (B) Verify the globule feature's ground truth. (C) The segmentation of features that our network has done.

METRIC / METHOD	SE	SP	AC	JA	DI
The Challenge's 2nd-best outcomes	0.117	0.997	0.989	0.063	0.118
proposed results from deep networks	0.119	0.997	0.991	0.060	0.108

Table II: Segmentation Evaluation Results for Dermoscopic Features

The Jaccard index (JA) is a statistic used to assess the degree of similarity and difference between sample sets.

$$JA=TP/(TP+FN+FP) \quad (5)$$

Dermoscopic feature segmentation has been assessed using the same measures. Figure 3 displays the split globule characteristic for an example picture.

The measurements that were chosen for this investigation are listed in Table 2. The results are similar to the second-best finish from the 2016 ISBI Challenge. The sensitivity of the suggested strategy is slightly higher, even if some

metrics are rather close to the results of the second-best group.

V. Conclusions

This work proposes two crucial segmentation tasks for melanoma diagnosis systems. We looked into a pre-trained model and a deep convolutional network using a semantic image dataset for this medical application. Several studies have yet to apply deep learning for dermoscopic feature segmentation, but not lesion segmentation. For both jobs, we employed the deep network architecture. Even though the outcomes of the proposed system are identical or slightly lower, the network's fine-tuning using a pre-trained model from the first job (lesion segmentation) minimizes the computation cost for the second task (feature segmentation), which is a promising conclusion for a hybrid model. Furthermore, we cropped test images for the second phase using the test masks produced by the lesion segmentation. It has also been shown that accuracy can be increased by using a deeper model and combining data from both high and shallow levels.

Despite being built on a basic hybrid model without the thorough fine-tuning necessary for Deep Learning implementations, the suggested approach produces some interesting results. Thus, there is potential for more advancement.

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