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Review of Deep Learning Based Segmentation and Recognition of Dermatological Images

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ABSTRACT

Dermatosis are prevalent across different age groups, and using deep learning methods to assist general practitioners can improve the accuracy of their diagnoses. This paper summarizes the applications of deep learning in the field of image processing, particularly in the segmentation and classification of skin disease images. First, it introduces the main deep learning models used in image segmentation and classification. Then, it provides a detailed overview of the specific applications and improvements of various segmentation and classification models in the task of skin disease image processing. By summarizing relevant studies, it demonstrates the significant advancements in accuracy achieved by deep learning in skin disease image processing. Finally, the paper concludes with a summary and offers prospects for the future of intelligent skin disease diagnosis.

KEYWORDS

Dermatological image segmentation; Dermatological image recognition; Deep learning

1. INTRODUCTION

Skin diseases have become the fourth leading non-fatal disease worldwide [1], affecting individuals of all ages and regions. The wide-reaching impact of skin diseases cannot be overlooked. Various factors contribute to the onset of skin diseases; different weather conditions, humidity levels, and dietary habits can directly or indirectly affect our skin [2], exacerbating the spread of these conditions. However, despite the high prevalence of skin diseases, there is a severe shortage of professional dermatologists. Often, a single dermatologist must serve many patients, leading to a significant imbalance in the doctor-patient ratio, which hinders the diagnosis and treatment of skin diseases. Therefore, accurate and rapid diagnosis of skin diseases is crucial for the effective treatment of these conditions.

With the aid of artificial intelligence (AI) technology, the medical image processing of skin diseases has become a critical area of interest, intersecting image processing, machine learning, and intelligent medicine [3]. Deep learning algorithms have advanced rapidly, with neural networks constructed from interconnected nodes that transmit input data and optimize the network through backpropagation to enhance performance [7]. These technologies have significantly improved the efficiency of tasks such as image classification, object detection, segmentation, and registration, providing a scientific foundation for the precise segmentation and classification of skin disease images. By employing these technologies, subjective factors in diagnosis can be minimized, resulting in more objective analysis and a more efficient diagnostic process. Consequently, using AI to achieve intelligent segmentation and diagnosis of skin diseases is imperative, aiding doctors in focusing on affected areas and providing disease classification reference information.

Currently, many researchers are engaged in the field of skin disease image processing. Segmentation, classification, and feature extraction are the three fundamental stages of lesion identification, facilitating the matching and analysis of skin lesions [6]. Neural networks, after extensive training, can accurately segment and classify skin lesion areas. This paper starts with the application of deep learning in image processing, summarizing the current research on deep learning methods for image segmentation and classification, and further reviews the progress in research on skin disease segmentation and classification.

2. IMAGE SEGMENTATION AND CLASSIFICATION BASED ON DEEP LEARNING METHOD

2.1. Image Segmentation Based On Deep Learning Methods

The primary goal of skin lesion segmentation is to delineate the critical affected areas, thereby excluding information from other skin regions and hair that may interfere with diagnosis. Currently, in the field of medical image segmentation, various researchers have proposed different methods. The U-Net network [4], for instance, introduced an encoder-decoder structure that employs convolution and pooling to extract key features from images, followed by deconvolution and upsampling operations to refine and restore the critical regions. In the same period, the Fully Convolutional Network (FCN) [5] was the first to implement an end-to-end semantic segmentation network using full convolution, allowing the network's input and output to have different sizes and enabling it to capture more detailed semantic information from the images.

For real-time image segmentation tasks, SegNet [8] utilizes a relatively lightweight structure to achieve better segmentation performance. Additionally, SegNet employs indexing information from the max-pooling stages during upsampling, making the final results more reliable and useful. Subsequently, the emergence of the DeepLab series models has significantly advanced image segmentation technology. Specifically, DeepLabV3+ [9] incorporates the Atrous Separable Convolution (ASPP) module, which greatly enhances the accuracy of semantic segmentation, though it requires higher hardware specifications for image processing devices.

2.2. Image Classification Based On Deep Learning Method

Focusing on the field of image classification, deep learning has achieved remarkable results in recent years, driven by continuous advancements in hardware. ResNet [10] introduced the innovative residual connection structure, addressing the issue of vanishing gradients in deep neural networks and allowing for deeper network layers. However, it still does not fully resolve the problem of overfitting during training. MobileNet [11] by incorporating the concept of tight connections, facilitated the transmission of information and gradients between layers, allowing for parameter sharing and improving computational efficiency. Nevertheless, this characteristic also leads to high memory demands during training, resulting in significant memory consumption. EfficientNet[12] through a compound scaling coefficient, improved the balance between computational efficiency and model performance, although it performs less effectively on small-scale datasets.

In recent years, the introduction of the Transformer architecture has significantly enhanced the extraction of image features by deep neural networks. Its multi-head self-attention mechanism maintains focus on complex task sequences and enables parallel processing of sequential data, thereby accelerating the training process. Building on the Transformer structure, many new image processing methods have emerged. Vision Transformer (ViT) [13] leverages the self-attention mechanism to capture global information across the entire image, though it also brings about greater computational complexity. The Swin Transformer [14] a deep learning model, introduces a windowed attention mechanism that divides the input image into fixed-size patches, applying self-attention within each patch. This approach drastically reduces the computational complexity associated with global self-attention mechanisms, achieving excellent results in image classification tasks.

3. SKIN LESION IMAGE SEGMENTATION AND CLASSIFICATION BASED ON DEEP LEARNING

3.1. Dermatological Image Segmentation Based On Deep Learning

The rise of deep learning has also led to advancements in medical image processing. In recent years, various strategies have been proposed by researchers for the segmentation of dermatological images. Maron et al. [15] demonstrated that feeding segmented skin images along with unprocessed images into a neural network does not degrade overall performance and helps eliminate the influence of extraneous skin factors. This has boosted confidence in the advancement of dermatological image segmentation techniques. Yanling et al. [16] developed a dataset and designed an image segmentation model based on fully convolutional networks to accurately diagnose the severity of vitiligo by segmenting facial vitiligo lesions. This model outperformed two dermatologists in segmentation accuracy. Chen et al. [17] constructed a recurrent attention convolutional network for segmenting dermatological images, achieving a Dice coefficient of 87.04% on the ISIC-2017 dataset. Zhao et al. [18] improved upon the U-Net++ architecture, creating a new model for skin lesion segmentation and introducing a novel loss function, resulting in excellent performance with a Jaccard index of 84.73%.

Zhang et al. [19] proposed a channel attention module (CMD) to fully utilize high and low-level feature information while reducing the semantic gap between the encoder and decoder, enhancing the robustness of the segmentation model. Their method achieved an accuracy of 95.7% on a dermatological segmentation dataset. Yanag et al. [20] utilized the DeepLabv3+ network model to detect and segment skin and lesion areas, showing that the network's segmentation results were comparable to manual cropping, greatly reducing the burden on doctors for data annotation. Wang et al. [21] introduced a collaborative learning deep convolutional neural network to obtain high-quality image segmentation labels for the segmentation network. They used lesion segmentation masks to provide contour information for the neural network, achieving a Jaccard index of 79.1% in lesion segmentation tasks. Anand et al. [22] combined the U-Net architecture with CNN for multi-class classification of skin diseases post-segmentation, reaching a classification accuracy of 97.96%. Minjie Gu et al. [23] proposed an intelligent segmentation model for skin lesions that integrates residual Inception and bidirectional convolutional gated recurrent units, achieving a Jaccard coefficient of 0.831 by leveraging the relationship between low-level and semantic features.

Since the introduction of the Transformer model, many researchers have incorporated this structure to enhance the accuracy of dermatological image segmentation. Zhang et al. [24] proposed a new CNN-Transformer hybrid structure based on an encoder-decoder architecture. They validated the effectiveness of their network through multiple metrics and conducted training and testing on seven datasets, including skin lesions, polyps, and glands. The proposed model achieved an IOU (Intersection over Union) score of 0.851 on the Glas dataset. Ghara et al. [25] combined CNN and Transformer structures to leverage the complementary strengths of both, creating a self-supervised skin disease segmentation network. They evaluated their model on publicly available dermatological lesion datasets, demonstrating outstanding performance.

3.2. Dermatological Image Classification Based On Deep Learning

The rise of deep learning has significantly advanced medical image processing, particularly in the field of dermatological classification, where various deep learning networks have substantially improved accuracy. Wang Shiwei et al. [26] enhanced the performance of the original ResNet50 model by integrating dilated convolutions and the SimAM module, achieving a 0.88% improvement.

Carcagn ìet al. [27] utilized geometric transformations such as rotation to process data and employed the DenseNet architecture combined with multi-level learning to automatically identify seven types of skin diseases, including melanoma and basal cell carcinoma, achieving an average accuracy of 82.6%. Jinnai et al. [28] used VGG-16 as the backbone network combined with the FR-CNN network, training a neural network for the classification of six pigmented skin diseases with an accuracy of 86.2%. Srinivasu et al. [29] built a neural network based on MobileNet V2 and conducted classification experiments on skin images from Kaggle, achieving an accuracy of 85.34%.

As network complexity increases, transfer learning methods are gradually being applied to deep learning networks. Wu et al. [30] focused on six common facial skin diseases, using five mainstream deep learning networks to apply transfer learning to their proposed model, achieving an average classification accuracy of 70.8%. He Xueying et al. [31] structured a deep convolutional neural network based on the VGG19 model, enabling the recognition of various pigmented skin diseases, with a recognition rate of 71.34%.

4. SUMMARY

Research on skin diseases has been ongoing, whether in the segmentation or classification tasks of skin disease images, with the aim of better addressing the issue of intelligent diagnosis of skin diseases. Many researchers have explored various solutions based on existing technologies, especially with the incorporation of artificial intelligence, leading to significant improvements in accuracy for such tasks. In this paper, various deep models for image segmentation and classification are first introduced, followed by a summary of different intelligent algorithms for skin image segmentation and classification based on these models. Currently, most intelligent skin disease segmentation and classification models still rely on strong supervised learning, which requires substantial resources for label creation. In the future, widespread application of unsupervised learning in intelligent recognition of skin disease images and even medical images will undoubtedly greatly advance the intelligence of this field.

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