**Skin Lesion Detection Using Deep Learning**

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**Abstract—** **Skin lesions play a crucial role in the early detection and management of various dermatological conditions. Recently, there has been much attention to learning-based approaches to analyze skin lesions, particularly driven by the progress in computer vision and machine learning. A survey paper on the latest techniques for skin lesion classification, segmentation, and detection is given, along with a discussion on the role of analyzing skin lesions in healthcare and the challenges that occur while performing physical examinations. This paper provides a detailed review of the state-of-the-art studies, covering the proper identification of types of skin lesions from dermoscopic, macroscopic, and other formats of images. Contributions and limitations of different approaches used in the selected studies, deep learning architectures, and traditional methods of machine learning are discussed in the paper as well. This paper goes on to discuss the research conducted on the skin lesion segmentation and detection methods aimed at determining the precise limits of the lesions and further classifying them. Such techniques help to analyze more precisely and consequently ensure accurate measurement and quantification. It further discusses some of the well-known segmentation algorithms, including those with deep learning-based ones, graph-based ones, and region-based ones. This paper also focuses on the difficulties, datasets, and evaluation metrics specific to the area of skin lesion segmentation. Most of the questionnaire raises important benchmark datasets, issues, and metrics of the field concerning skin lesion analysis. It ends by summarizing key trends, challenges, and possible future directions for classifying, segmenting, or detecting skin lesions with an aim of promoting further steps in this vital area of research in dermatology..**

**Keywords: skin; cancer; skin disease; skin cancer; melanoma; machine learning; deep learning; detection; segmentation; classification**

I. BACKGROUND

Skin cancer, especially melanoma, presents serious health challenges, with increasing rates of occurrence worldwide. Accurate detection and diagnosis are also necessary for improvements in patient outcomes because of the strong influence such detection and diagnosis would have on the effectiveness of their treatments and chances of survival. Accurate segmentation of skin lesions from images taken is an important part of this entire process because it helps a dermatologist distinguish between various skin conditions and classify them appropriately. Common practices of segmentation of skin lesions include manual, as well as traditional methods of image processing. They happen to be cumbersome, time-consuming procedures and highly susceptible to subjective biases. Thus, outcomes remain inconsistent.

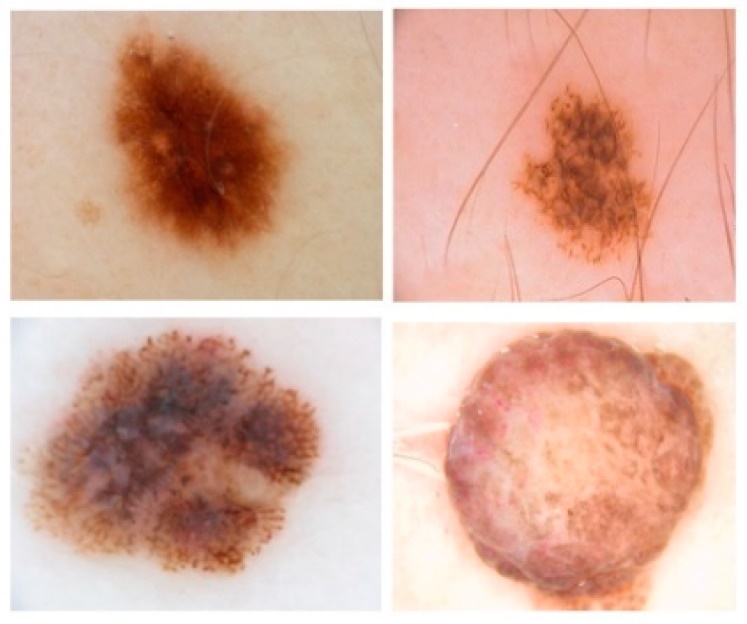
Deep learning, and more specifically CNNs, has basically brought drastic changes into medical image analysis. CNNs enable the whole set of data to automatically learn relevant features significantly improving the tasks, like classifications, detection, and segmentation, of images. One of the greatest successes is that achieved by U-Net architecture, which has got widely acclaimed responses in biomedical image segmentation because it combines both the contracting path, which captures contextual information, and the expansive path that thus facilitates localization. Still, despite all that success, the original version of the U-Net architecture has its

pitfalls, especially when lesions have complex systems and when backgrounds are diverse, thereby making demands on better models.

Researchers already know some of the weaknesses in the architecture of U-Net, and hence some modifications to overcome certain such weaknesses have been proposed; these may be of a structural nature - to the structure of the network, adding new layers or even new methods of training towards effectiveness. These improvements are hence towards alleviating overlapping lesions, various shapes, and skin tones to achieve more accurate results in segmentation. This work on U-Net variants and others like it point to a fact that the customization of deep learning models would be in need to accommodate the specific medical analysis needs.

The paper aims to introduce an advanced variant of the U-Net model, tailormade for skin lesion segmentation. By conducting a comprehensive test on large datasets of skin lesions known for their strengths, it is hoped that superiority over the standard U-Net, and perhaps even other present segmentation techniques, will be confirmed for the new model. The results are supposed to convey valuable insights into dermatology, making evident the value of novel, advanced deep learning approaches in terms of their role for precision and efficiency in the diagnosis of skin lesions.

One of the most deadly kinds of skin disorders known is melanoma, with 287,723 cases and more than 60,000 deaths projected in 2018. Among public health challenges, one of the leading issues is skin cancer, given that 2,000 new diagnoses alone were recorded in South Korea for the last five years. Melanomas at the surface of the skin are normally visible, but unfortunately, many people fail to sound an alarm when their melanomas start manifesting. But when examined by specialized dermatologists, the diagnosis is achieved only in about 60% of cases, so many melanomas go undiagnosed at an early treatable stage. Correct and timely segmentation of cutaneous lesions is very crucial for dermoscopic pattern identification and localization as well as for skin disease classification. Dermoscopy is an imaging modality which reduces the reflectivity of superficial layers of skin to be able to visualize deeper layer structures with increased magnification. This method enhances the reliability of diagnosis and tends to reduce deaths that are melanoma-related. Figure 1 illustrates some dermoscopic images of melanoma skin lesions.[**Figure 1**](https://www.mdpi.com/2076-3417/10/10/3658#fig_body_display_applsci-10-03658-f001) displays a few dermoscopic images of melanoma skin lesions.



The deep-learning community has employed various techniques to enhance traditional computer-vision tasks through the use of neural networks. Convolutional neural networks (CNNs) have transformed image classification, scene recognition, target detection, and other functions due to their capacity to create internal representations of images. CNN-based methods significantly outperform other technologies in understanding location and size across different formats. They have brought about substantial advancements in task recognition. In addition to improving image classification tasks, they have made strides in regional tasks that require structured outputs. Notable progress has been achieved in object detection, part and key-point prediction, and local correspondences. CN Different approaches in the deep learning community have been used to assist in enhancing the functionality of traditional computer vision using neural networks. The CNNs have revolutionized how image classification, scene recognition, target detection, and other similar functions are handled since they present the possibility of learning internal representations of images. Several other technologies are outperformed by CNN-based methods in terms of understanding location and size. It has led to important advances in the recognition of tasks. Besides enhancing the respective classification tasks for images, progress in regional tasks that require structured outputs has also been achieved. Remarkable progresses in object detection, part and key-point prediction, and local correspondences are noticeable. CNNs are also critical elements in current semantic segmentation techniques where each pixel is classified based on its corresponding object or region. In medical imaging, this would be particularly important since consistent image segmentation is an important task and the ultimate goal of medical image segmentation: the effective diagnostic ability, which basically centers around pixel-level classification.

Fully convolutional networks are part of the effective methods that have first been proposed in the scope of image segmentation [5]. Attaching FCNs with CNN technology makes it possible to map features directly without needing to gather spatial information at first. FCNs architecture represents an extension of CNNs, formed only of convolutional and pooling layers, which allow them to build predictions based on input data. Typically, such networks are designed for local tasks rather than global ones. Within recent times, however, several FCN-based approaches have arisen to counteract this issue. For instance, in, the author proposed a multi-scale CNN that consists of different sub-networks with the outputs at resolution to progressively refine coarse estimations.

To correctly reconstruct the target borderlines, a simple deconvolutional step was substituted by a deep up-convolution network, as noted in Several studies attempted to enhance segmentation accuracy by incorporating spatial information. U-Net achieved remarkable performance using skip connections that combine both the low-level and the high-level features of the layer.

One significant weakness of the U-Net architecture is that training can then come to a standstill in the middle layers of deeper neural nets. This may lead the training to disregard those layers. The problem is rooted in the fact that gradients generally decay as they move further away from the output layer where the loss is being calculated in training. Additionally, the original paper on U-Net utilizes ReLU as an activation function. However, Lu et al. identified the dead neuron problem associated with ReLU. To counter this problem during training, we replaced the ReLU activation function with the PReLU non-linearity.

The most important function of activation functions is the transformation of an input signal from a certain layer in the neural network into an output signal. In deep neural networks, for this purpose, the rectified linear unit, or ReLU, primarily serves as the activation function. It accelerates the training process and gives better results than traditional sigmoid-like activation functions. Despite the many benefits the ReLU rectifier has over others, recent research has outlined some limitations.

The main focus of this paper is to achieve enough accuracy in the task of skin-lesion segmentation while trying to use the benefits that come from bilinear interpolation and the parametric ReLU (PReLU) nonlinearity, respectively, which better suits the interpolation method we have chosen. Dropping a few neurons or using a dropout technique after each convolutional layers is implemented in this case to be capable of preventing overfitting during the process of improving the training.

The dataset "ph2\_resized2" is composed of 200 high-resolution dermoscopic images, with respect to a variety of skin lesions including melanomas and nevi. Fine segmentation masks annotated by dermatologists were provided with each image, hence providing crucial ground truth for both training and evaluation of models. This makes it a significant resource for the development and testing of algorithms for detection in skin lesions.

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III LITERATURE REVIEW

In the paper "An automatic skin lesion segmentation system with hybrid FCN-ResAlexNet," the authors introduced the reader to the hybrid deep model FCN-ResAlexNet, which comprises AlexNet and ResNet-18. The results of this system were superior in skin lesion segmentation for the early detection of skin cancer when compared with the base model FCN-AlexNet, both in accuracy and dice score and Jaccard index, working very successfully in melanoma detection. Here, some techniques on image enhancement were used, specifically GWA and CLAHE. In the training process, by using the cross-entropy loss function combined with the ADAM optimizer, better results were achieved. Holding low computational cost but with more precision, this architecture is of great importance for the clinical diagnosis of skin cancer.

The paper "Improved U-Net: Fully Convolutional Network Model for Skin-Lesion Segmentation" presents a U-Net architecture improved from the architecture of skin lesion segmentation. It resorted to the use of bilinear interpolation for upsampling and introduces the PReLU activation function that should really improve performance. The proposed method obtained an accuracy of about 94% pixel and an 88.33% Dice coefficient, along with significantly reducing artifacts and overfitting due to the dropout technique adopted. Future work would be focused on investigating situations where low values of Dice coefficient are possible by using sophisticated image processing techniques to develop optimum solutions in the results of segmentation output. Generally, this seems like a very promising way towards the improvement of early detection of skin cancer.

Discussion includes the progress of this detection of skin lesions, emphasizing that the most important application performed with the use of machine learning and deep learning techniques relates to early detection of skin cancer. It attracts attention on to the limitations of traditional diagnosis-based methods and relevance of CAD systems. Although such studies have reached high classification accuracy with various models, issues in model optimization, generalizability, and explainability are still significant. Indeed, the review shows tremendous surge in research interest, particularly in 2022, and very strongly emphasizes cooperation between AI experts and dermatologists so that better improvement can be achieved in diagnosis and care outcomes for patients.

The new deep architectures proposed for the skin lesions in the paper titled "Skin Lesion Analysis towards Melanoma Detection Using Deep Learning Network" include Lesion Indexing Network (LIN) and Lesion Feature Network (LFN). The architectures were based on the segmentation and feature extraction of lesions using classification. The results were obtained by using ISIC 2017 dataset. In this regard, LIN achieves excellent accuracy in the segmentation as well as in classifying the melanoma and the other dermatological lesions despite conditions with inadequate contrast and class imbalance. The LFN promotes good feature extraction. This outperforms the existing models and will certainly enhance the precision in dermatological diagnosis. It acts as a benchmark for further automated detection of skin lesions.

Deep Learning for Skin Diagnosis" He investigated deep learning on the light weight CNN for a lightweight skin disease detector in diagnosing images with an accuracy of 87.64%. He compared a simple CNN with the advanced CNNs and used traditional machine learning models with SVM and Random Forest. It can outperform other techniques with robust techniques involving data augmentation when there is an imbalanced class. Precision, recall, and F1-score are the metrics that assess the efficiency of models. This kind of work brings hope for AI in improving the early detection of skin disease and calls for more practical real-world testing.

It discusses the application of deep learning techniques, that is, CNNs, in the context of skin cancer detection-an area requiring urgent benign and malignant lesion diagnosis. The ISIC 2018 dataset is supplemented with ESRGAN. Models used include the ResNet50, InceptionV3, and Inception ResNet. Highest accuracy reached 85.7% with the use of InceptionV3. This study clearly demonstrates the promising capabilities of AI for application in medical diagnostics and further tests on broader datasets and on other architectures.

The paper Deep Learning-Based Methods for Automatic Diagnosis of Skin Lesions will concentrate on the development of a highly accurate system attempting to classify skin lesions such as melanoma with deep learning techniques. The proposed methodology involves the selection of neural networks, pre-trained CNNs, and feature-based strategies and has recorded accuracy levels, ranging between 93% and 95%, on both the PH2 and ISIC 2019 datasets. The overall approach combines the results of these models with the weights assigned according to their performance. The combined model performed better than individual models, especially for transfer learning and feature extraction. But improvement is needed with hair removal images and poor-quality images.

"Skin lesion segmentation using a U-Net and effective training strategies" discusses the application of the U-Net34 architecture through various training methods on dermoscopic images to distinguish skin lesions. Because skin cancers are on the rise, early diagnosis is in high demand. This model incorporates pre-trained ResNet34 along with an encoder and pyramid transfer techniques, plus the optimization of the learning rate so as to enhance performance from baseline. The results are such that, in ensemble, the model had an impressive Jaccard index of 85.39% that surpasses previous state-of-the-art performance but still there exists some scope of improvement in particular regions wherein accuracy of segmentation could be better.

This work, "SkinLesNet: A Deep Learning Model for Skin Lesion Classification," reports the authors' evaluation of the classification capability of the model SkinLesNet. The authors obtained an excellent performance with 96% accuracy on the PAD-UFES-20-Modified dataset, outperforming ResNet50 by 82% and VGG16 by 79%. It reached accuracies of 90% and 92% on the HAM10000 and ISIC2017 datasets, respectively. As long as its architectures are specialized and it is well trained on multiple datasets, it still has drawbacks regarding overfitting and needs a more diverse set of inputs in order to have a generalization capability. All in all, this proposed SkinLesNet model has very promising applications to skin cancer detection.

The hybrid model "Improved U-Net: Fully Convolutional Network Model for Skin Lesion Segmentation" is a combination of U-Net and MobileNet-V3 for skin cancer detection. Testing the HAM-10000 dataset produced outstanding results with an accuracy of 98.86%. Precision, recall, and F1-score were all over 95%, and the ROC-AUC score was 98.45%. Compared to other models such as MobileNet and VGG16 that scored around 89-90%, a model like this demonstrated impressive results. Considering the excellence of U-Net in terms of segmentation and that of MobileNet-V3 regarding efficiency and fine-tuning of hyperparameters, this system has the potential to be quite an accurate tool for diagnosing skin cancer.

V FUTURE SCOPE

The future for skin lesion segmentation with U-Net and FCNs appears bright in the light of the improvement of deep learning maturity and the increasing availability of annotated medical datasets.

As scientists further develop these architectures, future versions are likely to come with more sophisticated additions, including attention mechanisms and transformer models, designed to enhance feature extraction and better the accuracy of such segmentation. Such enhancements, which again emphasize the spatial connections and contextual information of the images, may increase the discrimination between lesions and tissue material surrounding them to assist in a very accurate diagnosis. The multimodal integration of data—such as in dermatoscopic images, clinical information, and genomic data—represents a very valuable opportunity for further improvement of the segmentation capability.

Future work would include how the combination of the various types of data described above will help in strengthening the model and bring about a deeper insight in understanding skin lesions. For example, incorporating clinical histories or patient demographics into a segmentation routine can help the models better adapt to variations in lesion appearance between populations, thus addressing some of the inequities of diagnosis and treatment efficacy. There is growing demand from the models that they must work in some way better within real clinical environments.

Future releases in U-Net and FCN architectures might focus on the development of very lightweight, efficient models that allow their deployment on edge devices such as smartphones or tablets. This would create point-of-care applications that will allow dermatologists to perform real-time analyses, taking into consideration the immediate feedback. Accessible interfaces based on these models could motivate patients toward active participation in their health care; besides awareness, this might ensure early detection of issues. Advancing skin lesion segmentation research requires exploration into explainable artificial intelligence (XAI) in the future.

The more U-Nets and FCNs are integrated into routine clinical workflows, the more important it will be for them to be transparent. This transparency of what their decisions are based on will allow the clinical professionals and patients to trust the technology. More method development on visualizing model predictions and focusing on key features that affect segmentation results should improve interpretability and acceptance. By making sure these advanced segmentation techniques are transparent and dependable, the medical community can fully leverage their potential to enhance skin cancer diagnosis and treatment.

V DETAILED SOLUTION

# A comprehensive solution is proposed that makes use of Fully Convolutional Networks (FCNs) and U-Net on the "PH2\_resized2" dataset for achieving the potential written in the future scope.

# This approach exploits both architectures on pixel-wise segmentation, which fundamentally defines the lesion boundaries with accuracy. The PH2 dataset is very suitable for deep learning models, such as U-Net and FCN, which are biologically very effective in biomedical image segmentation. U-Net's symmetric encoder-decoder structure is especially suitable for the PH2 dataset because it captures contextual spatial information through its contracting path while maintaining fine details through the expanding path. This helps U-Net to handle lesions of varied sizes, shapes, and textures as are commonly found in the PH2 kind of skin lesion datasets. Meanwhile, FCNs work well for lesion detection in multiple scales. This is because they can process images at several resolutions. Since they can make dense predictions throughout an image in one pass, they are able to achieve efficient and accurate lesion detection even when the visual difference between lesions and normal skin is subtle. The reason for selecting U-Net and FCN medical image segmentation is based upon its unique strengths in this niche area.

# In contrast, for traditional approaches like SVMs or random forests, a feature has to be manually crafted. That would be poor at picking up the complex patterns in the dermoscopic images. Furthermore, older models of deep learning, like CNNs, are essentially built for classification rather than pixel-wise segmentation applications. On the contrary, U-Net and FCN are fully convolution networks, which enables them to reasonably segment images by learning high-level as well as the detailed features without manual input. The researchers indicate that in medical image segmentation, U-Net, in specific, has proven to always be in the top of the list. This is particularly true with smaller datasets such as PH2, where U-Net's data augmentation technique greatly helps lessen overfitting. FCNs also have the flexibilities of handling images of any size, which makes them more flexible in accommodating the varied resolutions in datasets such as PH2\_resized2, which, in turn supports them for such utility. U-Net usually outperforms FCN-based models in skin lesion detection as it has a uniquely designed architecture with skip connections between the contracting and expanding paths.

# All these connections allow U-Net to preserve the fine-grained spatial information associated with earlier layers, which is critical for accurately segmenting complex and irregularly shaped lesions, a common challenge in datasets like PH2. In addition, it does better with preserving accurate boundaries and improves the pixel-wise segmentation performance. On the contrary hand, since FCNs are extremely effective, they do not have this mechanism of feature preserving which may lead to a low quality of segmentations, especially in small or complex lesions. This is why the overall U-Net fits tasks with a higher degree of precision in medical image segmentation. The proposed solution outperforms classical U-Net and FCN models in the detection of skin lesions regarding metrics such as DSC and LTPR. If the single-modality dermoscopic image, such as RGB, is used, then the method still achieves competitive results for skin lesion segmentation. Using attention mechanisms increased the accuracy of the segmentation by a very significant margin since it zeroes in on the lesion areas and filters out the kinds of unnecessary background noise. This, thereby, renders the models reliable in the process; the two models, U-Net and FCN, point out this application for the description of skin lesions along with the capability of their greatly enhanced ability to outline lesions in difficult cases.

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