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Literature Review: Skin Cancer Types Detection Using Deep Learning

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Abstract— **Skin cancer ranks among the swiftly proliferating diseases globally, exacerbated by the limited resources. Timely recognition of skin cancer holds paramount importance for precise diagnosis and identification, facilitating a preventative approach overall. The incidence of melanoma, the most perilous type of cancer of the skin, is increasing. Identifying skin cancer in its initial phases poses a challenge for dermatologists. Over the past few years, both supervised and unsupervised learning assignments have extensively employed deep learning techniques. Among these, Convolutional Neural Networks (CNN) has outperformed its counterparts in tests related to object detection and classification. The algorithm used here relies on a bank of directional filters (difference of Gaussians) and explores color, directionality and topological properties of the network. Dull Razor algorithm has been used to remove artifacts such as hair as they cause difficulties in detecting pigments.**

Keywords— Deep learning, Convolutional Neural Networks (CNN), Color analysis, Data Augmentation, Artifacts removal, Pigment detection.

INTRODUCTION

Detecting skin cancer is of utmost importance because of the critical impact it has on early treatment outcomes. Despite the challenges inherent in this process, the advent of deep learning, a subset of artificial intelligence, has revolutionized the field by significantly enhancing accuracy and accessibility. Using sophisticated computer algorithms, deep learning facilitates the meticulous analysis of skin images, this enables the identification of potential cancerous lesions. This advancement in technology not only augments the probability of early detection but also contributes to improved overall outcomes.

The process of the decision-making in skin cancer diagnosis has spurred advancement in algorithms specifically tailored for the analysis of lesions and the detection of melanoma. One pervasive issue in this domain is the presence of unwanted elements, such as shadows and hairs, in most skin-lesion images. These elements pose a considerable challenge, as they can obscure the accurate lesion segmentation, potentially introducing erroneous information about its characteristics.

To address these challenges, artificial vision techniques play an important role in eliminating noise components from skin lesion images. Among the factors influencing lesion segmentation, body hair stands out as a significant consideration. For instance, a pre-processing technique known as "Dull Razor" is employed for the purpose of detecting and removing hairs. This technique aids in refining the images as well as contributing to the overall reliability of subsequent diagnostic analyses.

In essence, the amalgamation of deep learning, artificial vision techniques, and specialized pre-processing methods like Dull Razor showcases the remarkable strides made in making diagnosis of skin cancer faster and more reliable. This multidimensional approach not only underscores the importance of early detection but also highlights the ongoing commitment to refining and advancing the technological landscape in dermatological healthcare.

DEEP LEARNING

As a part of our research, we intend to draw upon a diverse range of resources to enrich our understanding and analysis of programming. In the study mentioned in [3], the accuracy in undersampling and oversampling techniques was compared. The undersampling technique using DenseNet169 achieved an accuracy of 91.2%, while the oversampling technique employing ResNet50 yielded an accuracy of 83%.

The methodology in paper [6] involves training the model and also testing the model on prominent CNNs—Inception V3, ResNet50, VGG16, MobileNet, and InceptionResnet—for the seven-class skin-lesion classification images. The study concludes that the InceptionResnet model achieved the highest average accuracy of 91%, providing insights into the workings of various models in skin cancer detection.
The study's methodology in paper [1] involves a comparative analysis between a one-level classifier and a two-level classifier categorizes skin-lesions into normal, atypical, or melanoma. Additionally, the paper outlines future work, emphasizing the exploration and extraction of novel features, such as pigment network, with the aim of enhancing the accuracy of lesion classification. One of the study involves preprocessing clinical images to enhance their quality. Following this, The preprocessed images are fed into a basic Convolutional Neural Network. Since it is a deep learning model, the CNN inherently extracts distinctive features from the provided images. This strategy has the potential to enhance melanoma detection by capitalizing on the automatic feature extraction capabilities inherent in CNNs [4].

The classification method discussed in the paper [7] entails the utilization of algorithms like machine learning or deep learning to categorize lesion images into benign or malignant classes. The authors conduct a thorough survey of various algorithms, also including artificially created neural networks, support vector machines, k-nearest neighbors, random forest, and deep convolutional neural networks, to explore and evaluate their effectiveness in skin cancer detection.

The paper [2] introduces the DC-AC architecture, incorporating a Double-Condensing Attention Condenser into a self-attention neural network to enhance computationalefficiency.
Furthermore, the paper outlines future work, expressing the intention to iterate on the network architecturedesign. The goal is to refine the approach makes it more adaptable and generalizable, with a particular emphasis on extending its application to other forms of cancer beyond theinitial implementation.

In the paper [8] a methodology is proposed comprising a five-block dilated convolutional feature extraction phase, featuring varied dilation rates and filter sizes, followed by concatenation to build a comprehensive feature map. The subsequent classification phase incorporates two connected layers incorporating dropout, culminating in a SoftMax layer for the final output. Additionally, the study employs class activation maps to visually highlight regions of interest in the images. Metrics for evaluation, including accuracy, precision, recall, and F1-score, are employed to analyze the model's performance, with comparisons made against baseline models like VGG-16 and VGG-19.
The authors of paper [9] adopted Google's Inception v3 CNN architecture for their own CNN training and transfer learning. This architecture had been initially pretrained on the extensive ImageNet dataset, encompassing 1.28 million images across 1,000 object categories. The authors fine-tuned the parameters throughout all layers by removing the final classification layer and retraining it with their specific dataset. To optimize the network, they employed backpropagation, RMSProp, and augmentation of data techniques. Furthermore, the authors strategically utilized transfer learning to capitalize on the innate image features acquired by the pretrained network.

In the study on Skin-Lesion Classification in paper [10], a supervised learning approach was employed, leveraging pre-trained deep models as feature extractors and support vector machines (SVMs) as classifiers. The study extracted deep features from three distinct pre-trained networks—AlexNet, VGG16, and ResNet-18—utilizing various layers. Following these features, multi-class SVM classifiers were trained, and performance evaluation utilized the area beneath the ROC curve as the primary metric. The study employed PyTorch as the deep learning framework, scikit-learn as the machine learning library, and MATLAB as the programming environment. The paper recognized potential biases and limitations, specifically addressing constraints related to the use of small training patches, a restricted set of pre-trained networks, and a limited validation set. These considerations offer valuable perspectives on the study's scope and limitations, contributing to the transparency and interpretability of the research findings.

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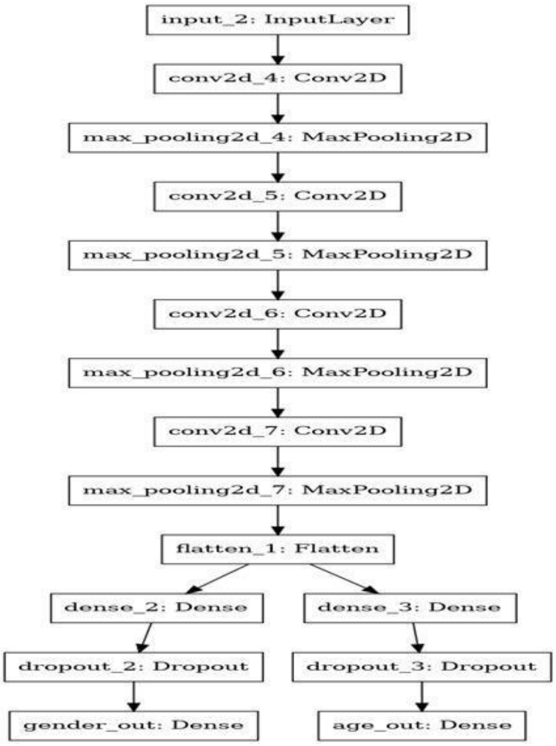

Figure 1. CNN architecture

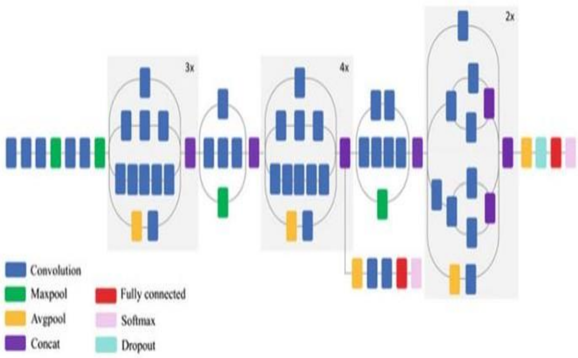

Figure 2. Inception V3 architecture

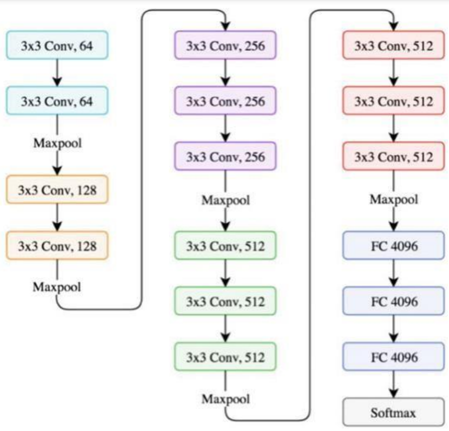

Figure 3. VGG 16 architecture

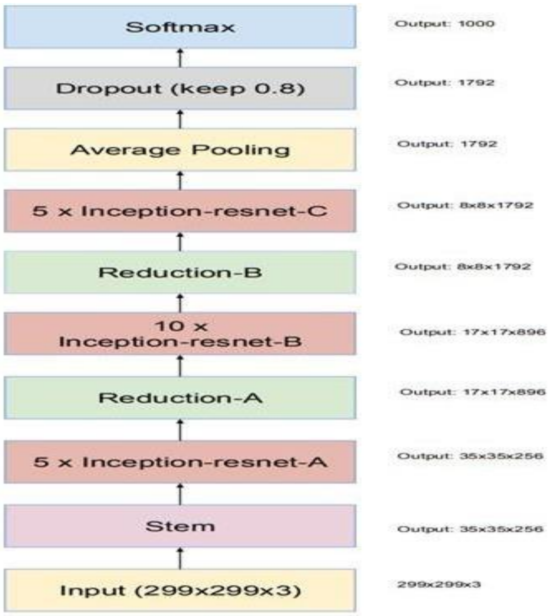

Figure 4. Inception-ResNet architecture

PREPROCESSING TECHNIQUES

Data augmentation is a crucial technique in machine learning as well as deep learning aimed at enhancing the diversity and size of training datasets. By applying various transformations to the existing data, such as rotations, flips, zooms, and brightness adjustments, data augmentation generates instances that are variations of the original samples while preserving their underlying information. The primary importance of data augmentation lies in its ability to address limitations posed by limited datasets. By artificially expanding the dataset, models are exposed to a broader range of scenarios, helping to prevent overfitting and improving generalization to unseen data. Moreover, data augmentation enhances the robustness of models by instructing them to identify patterns and features that remain unchanged under common transformations. This leads to models that exhibit greater resilience to variations, distortions, and noise inherent in real-world data, thereby culminating in enhanced performance and reliability across a spectrum of applications in both deep and machine learning [4] [5] [6] [10].

In skin surface images captured by digital cameras, challenges like illumination inconsistencies and noise arise from nonuniform lighting and reflections. To shed light on this in CNN training, which detects illumination effects through sharp changes in the saturation and value channels of the HSV color space. This correction eliminates illumination-induced distortions without compromising genuine edges. Additionally, a segmentation mask, produced using a k-means classifier (k = 2) on the preprocessed image, isolates the lesion's region. To minimize the impact of normal skin texture on classification, the segmentation mask is made to smooth areas outside the lesions with a Gaussian filter (σ = 2). Color analysis further refines preprocessing for accurate CNN training and lesion classification [4].

Image normalization is a critical preprocessing step in computer vision, involving the adjustment of pixel values to

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a standardized scale, often [0, 1] or [-1, 1]. This process mitigates variations in lighting conditions and pixel intensity, ensuring comparability between images from different sources. Normalization aids in the convergence of machine learning models, especially in neural networks, leading to improved performance, faster convergence, and enhanced generalization to new, unseen data [6].
The removal of noise process in [3] study adopts the Dull Razor method to effectively eliminate unwanted hair artifacts from skin images. By employing this method, the dataset undergoes a refinement that significantly enhances its quality, thereby facilitating more precise and reliable analysis. The removal of hair artifacts contributes to a cleaner and more focused dataset, reducing potential distractions and improving the overall integrity of the images. This careful method guarantees that subsequent analyses, such as pattern recognition or feature extraction, are conducted on a dataset of higher quality, promoting the accuracy and efficacy of the study's outcomes.

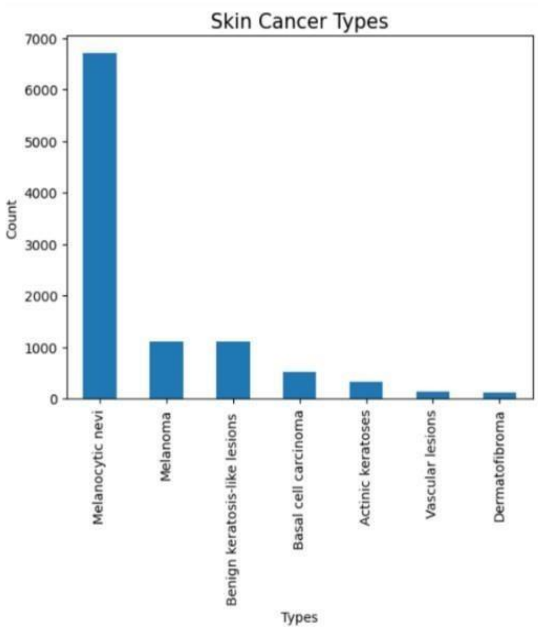

Figure 5. Data visualization

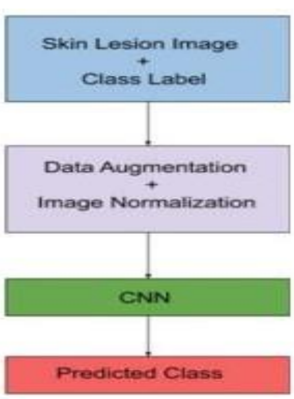

Figure 6. Classification model overview

Reference	ReLU	Swish
[1]	-	-
[2]	-	Y
[3]	Y	-
[4]	-	-
[5]	Y	-
[6]	Y	-
[7]	Y	-
[8]	Y	-
[9]	Y	-
[10]	Y	-

Table 1. The summary of functions used in different papers

Table 1 demonstrates 'Y,' implying the adoption of a specific activation function, while indicating otherwise signifies the absence of its utilization.

CONCLUSION

Reviewed literature on skin cancer identification through deep learning methods reveals a multifaceted landscape of diverse approaches and innovative techniques. Comparative studies shed light on the nuanced impact of sampling methods and the efficacy of different CNN architectures, providing valuable insights for optimizing classification models. The integration of pre-trained models, such as DenseNet169 and ResNet50, underscores the practicality of leveraging existing neural network architectures for enhanced efficiency. Preprocessing techniques, like segmentation masks and color analysis, address critical challenges in skin lesion images, emphasizing the importance of thoughtful data preparation for accurate model training. The introduction of novel architectures, like the DC-AC architecture, showcases a continuous pursuit of computational efficiency and paradigm shifts in neural network design for skin cancer identification. Acknowledging biases and limitations enhances the credibility of findings, while the strategic use of transfer learning underscores the significance of building upon established knowledge. Supervised learning approaches, exemplified by studies using multi-class SVM classifiers, provide robust frameworks for skin-lesion classification. The exploration of diverse metrics like precision, recall, accuracy and F1-score, emphasizes a comprehensive evaluation framework for skin cancer identification models. Overall, this body of research underscores the collaborative effort across deep learning, medical imaging, and dermatology, advancing the field and contributing to improved diagnostic tools for enhanced patient outcomes.

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