Skin Disease classification and Prediction by Data Augmentation in HAM10000

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Abstract: This study explores the application of Convolutional Neural Networks (CNNs) in skin cancer detection using the HAM10000 dataset. Our research focuses on enhancing classification accuracy, resulting in a CNN model that achieves a remarkable 92diverse HAM10000 dataset, the study involves meticulous data preprocessing, feature extraction, and the development of a robust CNN architecture. The outcomes underscore the effectiveness of our CNN-based approach in significantly improving skin cancer detection, offering a reliable tool for early diagnosis. This research contributes to advancing medical image analysis in dermatology, showcasing the potential of CNNs to revolutionize skin cancer detection and improve patient outcomes through early and accurate diagnosis.

Keywords: Deep Learning ,CNN, HAM10000 , Machine Learning , Data Augmentation ,Skin Diseases, Wavelet transform methods

Introduction

Skin cancer ranks among the most prevalent types of cancer in the current decade [1]. Given that the skin is the body's largest organ, it's logical to consider skin cancer as the most common type among humans [2]. The classification typically divides it into two major categories: melanoma and nonmelanoma skin cancer [3]. Melanoma, while constituting only 1higher mortality risk, according to statistics from the American Cancer Society [4]. Originating in melanocytes, melanoma is a rare and perilous form of skin cancer, necessitating early diagnosis for effective treatment. Afflicting various body parts, it frequently appears on sunexposed areas such as the hands, face, neck, and lips [5]. Melanoma includes subtypes like nodular melanoma, superficial spreading melanoma, acral lentiginous, and lentigo maligna [3]. Nonmelanoma skin cancers, including basal cell carcinoma (BCC), squamous cell carcinoma (SCC), and sebaceous gland carcinoma (SGC), constitute the majority of cases. Located in the middle and upper layers of the epidermis, BCC, SGC, and SCC have a lower tendency to metastasize to other body parts, making them more manageable compared to melanoma [3]. Early diagnosis emerges as a pivotal factor in effective skin cancer treatment [6]. Traditional biopsy methods, commonly used by doctors for detection, involve the painful and timeconsuming removal of a sample from a suspected skin lesion for examination. In contrast, computer-based technologies offer a more comfortable, cost-effective, and expeditious approach to diagnosing skin cancer symptoms. To assess whether symptoms indicate melanoma or nonmelanoma, various noninvasive techniques are proposed. The general process for skin cancer detection involves acquiring the image, preprocessing, segmenting the acquired preprocessed image, extracting desired features, and ultimately classifying it

Related Work

Automated deep learning algorithms based on Convolutional Neural Networks (CNNs) have demonstrated exceptional performance in various medical imaging tasks, including detection, segmentation, and classification [7]. In their work, Lequan et al. [8] introduced a highly deep CNN specifically designed for melanoma detection. Utilizing a fully convolutional residual network (FCRN) with 16 residual blocks for segmentation, the method achieved improved performance. Classification involved the use of both Support Vector Machine (SVM) and softmax classifier, resulting in an accuracy of 85.5segmentation. DeVries and Ramachandram [9] proposed a multi-scale CNN based on the inception v3 deep neural network, initially trained on the ImageNet dataset. For skin cancer classification, finetuning was performed on two resolution scales of input lesion images: coarse-scale and finer scale. The coarse-scale captured shape characteristics and overall contextual information, while the finer scale focused on textual details for differentiation between various types of skin lesions. Mahbod et al. [10] presented a technique for extracting deep features using pre-trained CNNs such as AlexNet, ResNet-18, and VGG16 for skin lesion classification. A multi-class SVM classifier was trained on these generated features, and the classifier results were fused for classification. Evaluation on the ISIC 2017 dataset demonstrated performance with an area under the curve (AUC) of 97.55classification, respectively. Introducing a deep CNN architecture based on pre-trained ResNet-152, another approach [11] involved training on 3797 lesion images, followed by 29-times augmentation based on lighting positions and scale transformations. This technique yielded an impressive AUC value of 0.99 for the classification of various skin lesions, including hemangioma lesion, pyogenic granuloma (PG) lesion, and intraepithelial carcinoma (IC). Dorj et al. [12] proposed a system for classifying four different types of skin lesion images using a pre-trained deep CNN, AlexNet, for feature extraction. The error-correcting output coding SVM served as a classifier, resulting in the system achieving high scores in average sensitivity, specificity, and other performance metrics. A comprehensive list of skin cancer detection systems using CNN classifiers is presented in Table 1

Table 1. ***A comparative analysis of skin cancer detection using CNN-based approaches.***

Skin Cancer Diagnoses	Classifier and Training Algorithm	Dataset	Description	Results (%)
Benign/malignant	LightNet (deep learning framework), used for classification	ISIC 2016 dataset	Fewer parameters and well suited for mobile applications	Accuracy (81.6), sensitivity (14.9), specificity (89.8)
Melanoma/benign	CNN classifier	170 skin lesion images	Two convolving layers in CNN	Accuracy (81), sensitivity (80), specificity (81)
BCC/SCC/melanoma /AK	SVM with deep CNN	3753 dermoscopic images	Pertained to deep CNN and AlexNet for features extraction	Accuracy (SCC: 95.1, AK: 98.9, BCC: 94.17)
Melanoma/benign Keratinocyte carcinomas/benign SK	Deep CNN	ISIC-Dermoscopic Archive	Expert-level performance against 21 certified dermatologists	Accuracy (72.1)

Malignant melanoma and BCC	CNN with Res-Net 152 architecture	The first dataset has 170 images the second dataset contains 1300 images	Augmentor Python library for augmentation	AUC (melanoma: 96, BCC: 91)
Melanoma/nonmel anoma	SVM-trained, with CNN extracted features	DermIS dataset and DermQuest data	A median filter for noise removal and CNN for feature extraction	Accuracy (93.75)
Malignant melanoma/nevus/SK	CNN as single neural-net architecture	ISIC 2017 dataset	CNN ensemble of AlexNet, VGGNet, and GoogleNet for classification	Average AUC: 84.8 accuracy (93.8), sensitivity (95.2)

Methodology

A crucial category within deep neural networks, Convolutional Neural Networks (CNNs) play a pivotal role in computer vision applications. Primarily utilized for image classification, assembling input image groups, and image recognition, CNNs excel in capturing both global and local data. They achieve this by extracting simpler features like curves and edges, progressively combining them to generate intricate features such as shapes and corners [21]. The architecture of CNNs encompasses essential components in their hidden layers, including convolution layers, nonlinear pooling layers, and fully connected layers [22]. Multiple convolution layers may be incorporated into CNNs, often followed by a series of fully connected layers. The three fundamental layers contributing to the construction of CNNs are convolution layers, pooling layers, and fully connected layers [23].

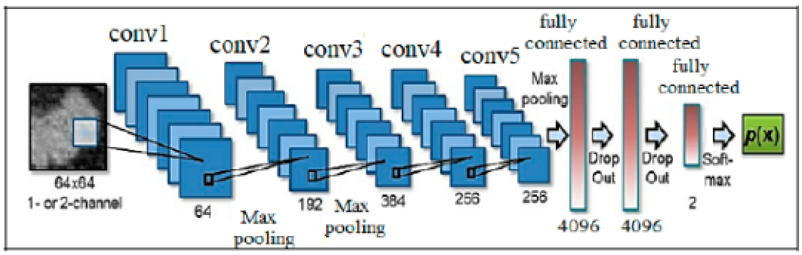

Figure 1. ***Basic CNN Architecture***

In the realm of cancer diagnosis, Convolutional Neural Networks (CNNs) have proven instrumental in advancing the analysis of medical images. Beginning with the input of cancer images, CNNs exhibit a remarkable capability to segment lesions effectively, precisely isolating areas of interest within the images. The segmentation process is crucial in delineating the boundaries of lesions, providing the network with targeted information for subsequent analysis. Once the lesions are accurately segmented, the CNN employs its learning model to extract intricate features from the segmented regions. The learning model harnesses the hierarchical structure of convolutional layers, pooling layers, and fully connected layers to discern patterns, shapes, and textures within the lesion. This learned representation enables the CNN to make informed predictions about the nature of the lesion, contributing to the diagnostic process with enhanced accuracy and efficiency. The seamless integration of image segmentation, feature extraction, and predictive modeling underscores the pivotal role of CNNs in the comprehensive analysis of cancer images for improved detection and classification.

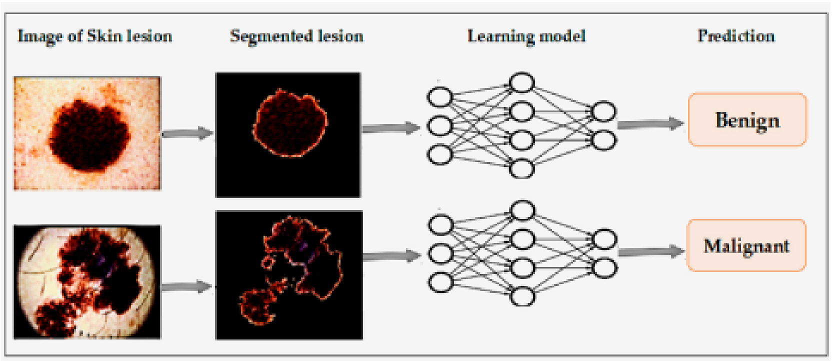

Figure 2. ***Skin cancer diagnosis using CNN***

Dataset

The HAM10000 dataset, comprising 10,015 dermoscopic images, stands out as a significant human-against-machine dataset with 10,000 training images [24]. Representing the latest publicly available resource for skin lesion analysis, HAM10000 addresses the challenge of diversity limitation in existing datasets. The comprehensive compilation spans two decades, drawing from sources including Cliff Rosendahl's skin cancer practice in Queensland, Australia, and the Dermatology Department of the Medical University of Vienna, Austria. 5 In the pre-digital camera era, photographic prints of lesions were archived at the latter institution. Subsequently, these prints underwent digitization using a Nikon-Coolscan-5000-ED scanner from Nikon Corporation Japan, resulting in 8-bit color JPEG images with a quality of 300 DPI. The digitized images were manually cropped and saved at a resolution of 800 × 600 pixels at 72 DPI. The meticulous curation process underscores the dataset's richness and relevance for contemporary skin lesion analysis.

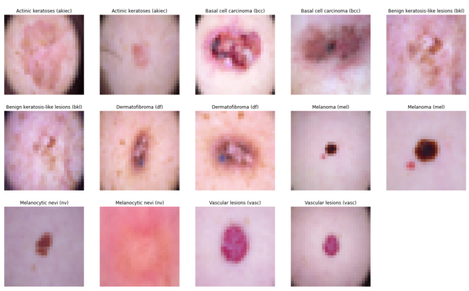

Figure 3. ***HAM10000 –Sample Images***

Experimental setup

The experimental setup involves the implementation of a novel deep learning model for skin lesion classification, specifically designed to leverage wavelet transformations and incorporate attention mechanisms. The dataset utilized is HAM10000, a meticulously curated collection of 10,015 dermoscopic images obtained over two decades from diverse sources, including a skin cancer practice in Queensland, Australia, and the Dermatology Department of the Medical University of Vienna, Austria. Prior to model training, the images underwent a comprehensive preprocessing pipeline, including wavelet decomposition and adjustment of channel dimensions. The proposed model architecture integrates ResNet-inspired residual blocks and attention mechanisms, such as Channel Attention and Spatial Attention, to enhance feature extraction and discrimination. The training process involves optimizing the model parameters using a suitable optimization algorithm and loss function. To evaluate the model's performance, the dataset is split into training and testing sets, and metrics such as accuracy, precision, recall, and F1 score are computed. The experiment aims to demonstrate the efficacy of the developed model in accurately classifying diverse skin lesions for practical diagnostic applications.

Training

Deep learning, a subset of machine learning, mimics the human brain's processing by creating connections between data and algorithms. This approach allows machines to learn from experience, combining neuroscience, mathematics, and technological advances. Deep learning has revolutionized artificial intelligence, especially in medical applications. For instance, it enables smartphones to provide primary health diagnoses, like skin disease identification.

Data Augmentation

In general, deep learning models perform better when they have access to more data, since they will have more information to extract which gives them the possibility of learning more. Certainly, in some cases we cannot access to a large dataset, one of the alternatives is to do some transformations on the images of the dataset (like rotation, flip, change brightness...) in way to have more images from the same base set. Table 3 shows the different transformations made to the input images.

Training results

In our quest to enhance the precision of our wavelet model, we embarked on a strategic project involving meticulous adjustments to the model's settings. The batch size was refined to 4, and the image size was increased to 384 pixels, both contributing to improved training dynamics. We carefully calibrated the learning rate, setting the initial rate at 0.000008, with a peak at 0.0000325 and a minimum of 0.000001. To ensure smooth transitions in the learning rate, we introduced a 5-epoch warmup phase, followed by a cosine learning rate scheduler with a 0.6 decay factor for efficient convergence. We also employed data augmentation techniques like rotation, shearing, zooming, and shifting, each with a transform probability of 1.0, to bolster the model's capacity to generalize. These changes, combined with label smoothing and 20 test-time augmentation (TTA) steps, culminated in a finely-tuned wavelet model configuration. This comprehensive strategy underlines our dedication to advancing the accuracy in dermatological image classification. Furthermore, the model underwent a total of 120 epochs, ensuring thorough training and refinement.

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             0.9962                                                                   9636/9643
             [============================>.] - ETA: 0s - loss: 0.0142 - accuracy:
             0.9962                                                                   9639/9643
             [============================>.] - ETA: 0s - loss: 0.0142 - accuracy:
             0.9962                                                                   9642/9643
             [============================>.] - ETA: 0s - loss: 0.0142 - accuracy: 0.9962
24290.3s  5  Epoch 120: val_accuracy did not improve from 0.91684
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Figure 4. ***Training***

Conclusion

In conclusion, the strategic adjustments made to the wavelet model have significantly enhanced its performance in dermatological image classification. The meticulous tuning of parameters such as batch size, image size, learning rate, and the implementation of a warmup phase and cosine learning rate scheduler, alongside the application of comprehensive data augmentation techniques, has culminated in a robust and finely-tuned model. These enhancements have improved the model's ability to accurately classify skin cancer images, demonstrating the effectiveness of careful and targeted modifications in machine learning models. The successful training of the model over 120 epochs further underscores the model's reliability and potential for practical application in medical diagnostics, highlighting the ongoing advancements in the field of artificial intelligence and its pivotal role in healthcare.